

**IMPROVING SPECIES DISTRIBUTION MODELS
USING EXTREME VALUE THEORY AND CLIMATE
DATASET ENSEMBLES**

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ABSTRACT

The development of climate datasets at fine spatial and temporal scales has commonly been driven by the need to better understand vegetation distributions and ecological systems. While a wide range of global, national and regional climate datasets have been developed over the last two decades, they are rarely compared directly in the ecological literature. This thesis evaluates a range of climate interpolation techniques and investigates how the spatial and temporal characteristics of climate datasets may be utilised to improve the predictive performance of plant species distribution models (SDM).

A series of spline-based and geostatistical methods for interpolating temperature variables are first compared across Victoria, southeast Australia. Secondary predictors (thermal remote sensing data and local topographic indices) which indirectly capture mesoscale microclimate and cold air drainage regimes were found to improve monthly mean minimum temperature interpolations by up to 39%. Thermal remote sensing data only reduced root mean square error (RMSE) by up to 6% for maximum temperature across Victoria and was most effective during the summer months. The interpolation methods used in southeast Australia were subsequently transferred to the Royal Himalayan Kingdom of Bhutan to validate their effectiveness in a novel climate. In Bhutan, the predictive performance of minimum temperature interpolations was also improved considerably (up to 23% reduction in RMSE) when using thermal remote sensing data and local topographic indices as spatial covariates. Thermal remote sensing data also reduced the RMSE for maximum temperature interpolations by up to 16% in Bhutan.

Interannual variability of climate extremes were used to evaluate how the temporal characteristics of climate may be used to improve the predictive performance of SDMs. Generalised Extreme Value (GEV) distributions were fitted to monthly climate data to generate variables which account for the skewed distribution of extremes. Models incorporating interannual variability (drawn from a range of expected return intervals) improved predictive performance compared to models using seasonal extremes only for 28 of 37 species assessed. Iteratively fitting models using alternate expected return intervals typically acted on the leading and trailing edges of current distributions, indicating that such methods may be useful for model calibration and characterising climate-driven source-sink population dynamics.

The impact of spatial disparities in climate on the predictive performance of plant SDMs was evaluated using three distinct datasets developed for Victoria as part of this research, in addition to two global datasets (WorldClim v1 and v2). Individual models were compared against one another and as ensembles to explore the potential for alternate predictions to complement one another. The Victorian datasets demonstrated a significant improvement over the original WorldClim dataset (up to 17.3% mean increase in D^2) and trended towards an improvement relative to WorldClim v2; however, no significant differences were found when comparing the alternate Victorian datasets. Multi-model ensembles achieved a mean increase of up to 13.8% and 29.2% in D^2 relative to individual models when using regional and global datasets, respectively. Ensembles provide a pragmatic method to improve the predictive performance of SDMs and allow a trade-off between the uncertainties and potential biases embedded in competing climate datasets.

DECLARATION

This is to certify that:

- i. the thesis comprises only my original work towards the Doctorate of Philosophy except where indicated in the Preface,
- ii. due acknowledgement has been made in the text to all other material used,
- iii. the thesis is fewer than 100 000 words in length, exclusive of tables, maps, bibliographies and appendices.

Stephen Blair Stewart

PREFACE

Portions of the research presented in this document have been published in collaboration with other researchers and published in peer-reviewed journals. For all manuscripts, I am the lead author and the principal contribution is my own. The nature of the contribution of co-authors is acknowledged as follows:

Chapter 2 published as

Stewart SB, Nitschke CR. 2017. Improving temperature interpolation using MODIS LST and local topography: a comparison of methods in south east Australia. *International Journal of Climatology* **37(7)**: 3098–3110. doi: 10.1002/joc.4902.

SBS and CRN conceived the ideas and designed the methodology; SBS collected the data, performed all analyses and led the writing of the manuscript; SBS and CRN contributed critically to drafts and the final manuscript.

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SBS and CRN conceived the ideas and designed the methodology; SBS and KC collected the data; SBS performed all analyses and led the writing of the manuscript; all authors contributed critically to drafts and the final manuscript.

Chapter 4 is unpublished material not submitted for publication as

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SBS, CRN and JE conceived the ideas and designed the methodology. SBS analysed the data and led writing of the manuscript. SBS, CRN, JE, MF, SK, SHR and LB contributed critically to drafts. All remaining authors, in addition to CRN, MF, SK and LB provided plot data critical to the analysis.

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SBS, CRN, and JE conceived the ideas and designed the methodology; all authors were involved in the collection or pre-processing of data; SBS performed all analyses and led the writing of the manuscript; all authors contributed critically to drafts and the final manuscript included in this thesis.

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1

CHAPTER ONE: INTRODUCTION

1.1. MOTIVATIONS

Climate and weather datasets are essential resources for calibrating ecological models and predicting the distribution of biological communities. Recent years have seen a diversity of climate datasets developed and made freely available online. These developments provide an opportunity to build better ecological models, but also present a considerable challenge. Despite strong conceptual underpinnings, with decades of research and statistical evaluation, competing modelling techniques can lead to disparate representations of climate and weather. The variety of methods, spatial extents (i.e. regional to global), spatial and temporal grains (e.g. 250 m versus 50 km grid cells; 6-hourly versus long term averages), and weather station networks used for generating such datasets mean that a quantitative comparison of their relative strengths and weakness is rarely possible. Climate dataset selection in ecological research is therefore most frequently a qualitative process guided by common practice and perceived data quality in a study region.

This thesis is motivated by the need to better understand the link between the spatial and temporal characteristics of climatic predictors and their influence on predicted species distributions. Many of the datasets that are available for ecological modellers are impacted by a trade-off between spatial and temporal grain. For example, datasets such as WorldClim (Hijmans et al. 2005; Fick & Hijmans 2017) or CHELSEA (Karger et al. 2017) have a high precision (approx. 1 km grid cells) but are only long term mean climatologies. Conversely, the monthly time series generated by the Climatic Research Unit (CRU; Harris et al. 2014) have much lower precision (approx. 50 km grid cells) but describe temporal trends from 1901 through to the near present. Few datasets capture temporal variability in conjunction with enough spatial precision to represent critical environmental gradients, such as temperature lapse rates, in regions of complex topography. Furthermore, a considerable number of decisions must be made regarding the selection and application of interpolation algorithms, collation and pre-processing of weather station observations, and the choice of supporting datasets, each of

which can have considerable impact on the final product. By developing a better understanding of how correlative species distribution models are influenced by temporal trends and spatial disparities in climate, we may improve our knowledge of current biogeography and thus our ability to effectively manage ecosystems and anticipate responses to future change.

1.2. CONTEXT

1.2.1. NICHE CONCEPTS AND SPECIES DISTRIBUTION MODELS

Niche concepts have evolved alongside the development of ecology as a scientific discipline. Hutchinson (1957) described the fundamental niche as a multidimensional hypervolume that is made up of elements critical to the survival of an organism. Factors such as dispersal barriers, interspecies competition and disturbance further restrict this space, and therefore the observed natural distribution of a species typically forms a much smaller subset of the fundamental niche. The modern concept of the realised ecological niche (or simply ecological niche) can be generalised as the sum of biotic and abiotic factors that allow a species to survive without immigration (Townsend Peterson 2006). Niche concepts and definitions can also be specific to the life history of the species. For example, the regeneration niche (Grubb 1977) describes the conditions that allow for the production and dispersal of viable seed, germination and establishment of seedlings, and the development of the juvenile plant. These conditions are specific to the ability of a species to regenerate and are not necessarily the same as those required for the mature organism to persist. Species distribution models (SDMs) include a broad suite of techniques for predicting the occurrence, abundance or vital rates of organisms based on the niche space that they inhabit, and have applications in pest management, conservation, biodiversity studies, and climate change analyses (Elith & Franklin 2013). SDMs can typically be characterised as either one of two classes; mechanistic (or process-based) models, and correlative models.

1.2.2. MECHANISTIC SPECIES DISTRIBUTION MODELLING

Mechanistic species distribution models require an explicit understanding of an organism's biophysical requirements and the environmental conditions that typically represent the fundamental niche (Kearney & Porter 2009). These models assess the biophysical thresholds of the organism against the external environment to determine the ability of the

species to survive. They do not require geolocated species observations or assume that organisms persist in equilibrium with their environment, and there is little ambiguity in the selection of variables that drive predictions as the critical dependences are already well understood (Sutherland & Maywald 1985; Pearson & Dawson 2003; Nitschke & Innes 2008; Kearney & Porter 2009; Kearney et al. 2010; Mok et al. 2012). Since these models typically represent the fundamental niche, they are useful for evaluating habitat suitability in the absence of complex biotic interactions, disturbances, or dispersal barriers. Process-based simulations are a subset of mechanistic models. They simulate competition and disturbance processes by simplifying complex biotic and abiotic interactions. Examples of these simulations include LANDIS-II (Scheller et al. 2007) and forest gap models such as HYBRID (Friend et al. 1997), JABOWA (Botkin et al. 1972) and SORTIE (Ménard et al. 2002). These simulation models assist in mechanistically bridging the gap between the fundamental and ecological niche; however, they have been criticised for their assumptions and oversimplification of complex ecological dynamics (Bugmann 2001). While mechanistic models can be reliably transferred to novel situations (e.g. climate change scenarios or new continents) and have the advantage of directly linking the functional traits of organisms to their environment (Kearney et al. 2010; Webber et al. 2011; Mok et al. 2012), they have intensive data requirements and require large investments in time and resources to develop.

1.2.3. CORRELATIVE SPECIES DISTRIBUTION MODELLING

Correlative models use statistical inference to link the presence, absence or abundance of species to environmental conditions (Elith & Franklin 2013). The complex array of biotic and abiotic interactions that comprise the realised ecological niche are inferred as part of the modelling process, as the realised distributions are used to calibrate these models. Correlative SDMs are highly flexible and can utilise a broad range of proximal variables such as those derived from remote sensing (Farrell et al. 2013; He et al. 2015; Fedrigo et al. 2019 Leitão & Santos 2019) that can be informative but not well suited to mechanistic models. Furthermore, while these models benefit from detailed knowledge of specific parameters that characterise the niche, it is not a strict pre-requisite as the predictor variables do not define but rather act as indirect proxies for causality (Austin 2007, Elith & Franklin 2013). This means that the distribution of less-studied species and large assemblages of records from biodiversity databases can be used to rapidly predict likely distributions with predictors that are

hypothesised to define the niche, without the need to pre-define complex biophysical relationships (Kearney & Porter 2009). The flexibility and generality that is provided by correlative SDMs make them a popular and useful tool for predicting species distributions.

Correlative SDMs are associated with a broad range of assumptions and challenges that differ from those of mechanistic models. One of the key assumptions is that the species being modelled is in equilibrium with its environment (i.e. the realised niche is fully occupied and stable in space and time). While in many cases this assumption may be acceptable (Pearson & Dawson 2003), there are various potential reasons why the realised distribution of organisms may be in varying states of equilibrium (Araújo & Pearson 2005). For example, species may not have fully dispersed and reached their potential distribution given the extent of suitable conditions available (Elith et al. 2010; Václavík & Meentemeyer 2011, Gallien et al. 2012; Coops et al. 2016). Dispersal limitations and shifting climatic regimes may also influence habitat suitability such that current distributions are not in equilibrium with environmental conditions (Svenning & Skov 2004). Correlative models also require that the realised ecological niche has been adequately sampled. Sampling issues have long been recognised as a challenge for correlative SDMs (Elith & Franklin 2013). Ideally, models are calibrated using systematically sampled plot data (including recorded presences and absences) across a broad gradient of environmental conditions so that species responses may be adequately characterised and modelled (Cawsey et al. 2002). Spatial autocorrelation (SAC) has also long been recognised as an issue; however, it is difficult to address (Dormann et al. 2007). SAC can have a strong influence on model parameters as species records are frequently located close to one another or in clusters, which violates assumptions around the independence of residuals. Algorithms such as generalised least squares (GLS) regression and auto-logistic models (e.g. Dormann et al. 2007; Crase et al. 2012; Crase et al. 2014) attempt to deal directly with spatial autocorrelation structures in the modelling process. Incorporating spatially blocked cross-validation strategies can also better reflect the ability of SDMs to extrapolate into new space by limiting the effects of spatial autocorrelation on model evaluation (Roberts et al. 2016; Valavi et al. 2018). A wide range of further topics have also been studied in the correlative SDM literature, ranging from the ecological relevance of predictors (Austin & Van Neil 2011), algorithm performance (Elith et al. 2006; Qiao et al. 2015), spatial grain (Guisan et al. 2007; Franklin et al. 2013) and temporal variability (Zimmerman et al. 2009; Bateman et al. 2012; Bateman et al. 2015) of prediction surfaces, multicollinearity of covariates (Dormann et al. 2012) and species detectability (Kéry et al. 2010), to comparisons of mechanistic and

correlative modelling outcomes (Elith et al. 2010; Briscoe et al. 2016) and community-level biodiversity modelling methods (Ferrier et al. 2007; Mokany & Ferrier 2011), among others.

The choice of algorithms used in correlative modelling and the strength to which the assumptions and limitations apply is partially dependent on the type and structure of data that is used in the modelling process. Systematically sampled data with records of both presence and absence is highly desirable for modelling species distributions as sampling biases can be minimised, absences are verified (although detection is never guaranteed; Kéry et al. 2010), and environmental gradients are suitably represented; however, this is not always feasible (Elith & Franklin 2013). SDMs are therefore often fitted with incomplete information, use a mosaic of plot data from different field studies to maximise sample sizes, or rely upon occurrence records from herbarium collections or biological databases. Many of the methods developed for use with both presence and absence data have also been applied using occurrence records (e.g. Engler et al. 2004) by generating pseudo-absences (i.e. random samples used as absences beyond a certain distance from occurrences) or by randomly sampling the domain of the spatial covariates (i.e. a background sample). This provides a contrast between suitable and potentially unsuitable conditions but should be avoided wherever presence-absence data is available (Wisz & Guisan 2009). Convenience sampling of occurrence records is a pragmatic way to build large catalogues of biodiversity observations and plays an important role in modelling species distributions; however, these records can lead to large systematic biases in model training data (e.g. reflecting road networks, rather than the true realised distribution) and need to be treated with care (Barbet-Massin et al. 2012; Kramer-Schadt et al. 2013; Fithian et al. 2015). While there are a broad range of methods that require presence and absence records (e.g. Elith et al. 2006), only a small number of techniques have been developed to use occurrence data exclusively.

1.2.4. CORRELATIVE ALGORITHMS

Simple bioclimatic envelope methods such as BIOCLIM (Nix 1986), HABITAT (Walker & Cocks 1991) and DOMAIN (Carpenter et al. 1993) were among the earliest attempts to project the niche of species into geographic space. Each of these methods can be applied with occurrence records, and do not strictly require a background sampling or pseudo-absences. These models were developed to better understand species distributions by using improved

climate interpolation techniques in conjunction with known occurrence locations (Booth et al. 2014). The BIOCLIM method fits a series of envelopes to variables that identify the range of environmental conditions (typically climate) that co-occur with species observations. The earliest application of BIOCLIM was a study of the distribution of 76 snake species across Australia (Nix 1986). While appealing in simplicity and ease of application, the method can be limited in that predictors are considered on independent axes and suitability is typically inferred within a specific range of a variable (e.g. minimum, maximum or percentile range). This can lead to the exclusion or inclusion of similar or dissimilar sites (depending on how the core suitable conditions are classified), respectively, particularly as the number and complexity of covariates increases (Carpenter et al. 1993). The HABITAT model was developed in response to some of the limitations of BIOCLIM (Walker & Cocks 1991). A reduced set of predictors is optionally first selected by identifying those variables that best separate known presence and absence locations via decision trees. The environmental envelope is then identified by fitting convex hulls (i.e. a polygon) to species occurrences across predictors, rather than the simple range-based approach used by BIOCLIM. While HABITAT was shown to perform favourably against BIOCLIM and a direct application of a CART (Walker & Cocks 1991), the convex hull procedure can lead to overfitting such that the predicted distribution reflects the observation locations directly rather than the desired niche space itself (Carpenter et al. 1993). The DOMAIN method was developed to address the limitations of both BIOCLIM and HABITAT by using pixel-by-pixel, numerically continuous comparisons of site similarity. Site similarity is computed by the Gower distance (Gower 1971), which produces a similarity score for each pixel evaluated. One of the major limitations of these simpler models is that the selection and relative contribution of environmental variables cannot be weighted appropriately without a method of separating suitable and unsuitable locations in environmental space. While the HABITAT method demonstrated the potential for CART models to inform variable selection, this process requires presence-absence data to be obtained, which when accessible is far better suited to regression and machine learning algorithms than simple bioclimatic envelope models.

Regression methods have been (and continue to be) widely used for modelling ecological phenomenon. Generalised Linear Models (GLM; McCullagh & Nelder 1989) are particularly useful, as they allow for non-Gaussian error distributions via a link function. This enables the fitting of models to probability and frequency based ecological responses by using binomial (i.e. logistic regression) and Poisson link functions, respectively. While ecological measures such as stem density or the probability of species occurrence have in many instances

been fitted using linear terms, these variables will frequently respond to predictors with a curvilinear trend (Austin et al. 1990; Austin et al. 1994). Characterising these curvilinear responses is critical to building effective and ecologically realistic models (Austin 2002). Generalised Additive Models (Hastie & Tibshirani 1986) extend GLMs by using smoothing functions in place of model coefficients, and therefore allow for the fitting of complex response functions. Multivariate Adaptive Regression Splines (MARS; Friedman 1991) are closely related to the GAM and can be used to model the contribution of independent variables across many species simultaneously (Elith & Leathwick 2007). Classification and regression trees (CART; as used by DOMAIN; Breiman 1984) can also be a simple and effective tool for modelling ecological response functions. CART models are highly interpretable (branching tree structure can be easily visualised), can characterise threshold responses and interactions, but can be sensitive to the training data and are not always effective with numerically continuous variables (Elith & Franklin 2013).

Machine learning techniques have emerged as powerful tools for predicting species distributions that typically perform well, are robust to noisy data and allow for non-linear responses but can be difficult to interpret (Bhattacharya 2013). These models include Genetic Algorithms for Rule-set Production (Stockwell & Peters 1999), Artificial Neural Networks (ANN; Manel et al. 1999), Random Forests (RF; Breiman 2001), Boosted Regression Trees (BRT; Elith et al. 2008) and MaxEnt (Phillips et al. 2006; Elith et al. 2011). Model ensembles, variable selection, subsampling processes, and decision trees are core concepts in machine learning methods that have shown potential in several studies to outperform the traditional approaches to species distribution modelling (Elith et al. 2006; Hernández et al. 2006; Wisz et al. 2008). MaxEnt is a popular machine learning algorithm that is designed for use with occurrence records; however, it is not a truly occurrence-only method as it relies on background samples for model calibration (Phillips et al. 2009; Elith et al. 2011). RF and BRT combine bootstrapping (i.e. repeated subsamples of the training data) and bagging (i.e. combining models fit to bootstrapped samples in an ensemble) with CART methods for model fitting. RF fits each contributing CART model randomly and independently. BRT iteratively fits CART models such that the loss function (e.g. deviance) is minimised, with each tree being dependent upon those fitted prior to the current iteration (Elith et al. 2008). Both RF and BRT benefit from the strengths of CART but minimise prediction variance by combining many models from subsets of the training data. Machine learning methods have been applied with great success

across many disciplines, including species distribution modelling; however, the performance of any technique is always limited by the quality of data used to train the model.

1.2.5. SPATIAL PREDICTORS OF SPECIES DISTRIBUTIONS

A wide range of variables are used for correlative modelling of species distributions. The persistence of vegetation across a landscape, for example, is dependent upon heat, energy and hydrological balances that are driven by local topographic, edaphic and climatic conditions (Adams 2010). Temperature and moisture variables are critical for modelling plant distributions, and while soil properties, geology, topographic position and solar radiation can describe fine scale heterogeneity of species responses and are undoubtedly of importance, they are less frequently used as predictors (Austin & Van Neil 2010). The uncertainty associated with gridded soil data products (e.g. Grundy et al. 2015) and complex interactions between solar radiation, topography (e.g. Wilson & Gallant 2000) and canopy structure (e.g. Campbell 1986) potentially limits their use as predictors of species distributions at fine scales. Remote sensing data is increasingly being used in ecological modelling applications. Examples include vegetation and moisture indices derived from optical imagery (He et al. 2015; Fedrigo et al. 2019) and structural characteristics of ecosystems using lidar (Fedrigo et al. 2018; Fedrigo et al. 2019) and radar (Bae et al. 2019) imaging. While each of these variables provide modellers with a valuable resource for studying very fine scale prediction, climate has long been understood to be the dominant driver of species distributions at broad spatial scales (Nix 1986; Austin & Van Neil 2010; Elith & Franklin 2013; Booth et al. 2014).

The development of climate datasets has historically been driven by the need for suitable spatial predictors in ecological modelling applications (Hijmans et al. 2005; Kriticos et al. 2011; Booth et al. 2014; Krager et al. 2017; Abatzoglou et al. 2018). Climatic predictors of species distributions are often expressed as bioclimatic variables derived from interpolated temperature, precipitation, vapour pressure and solar radiation datasets. Many of these indices were originally developed for BIOCLIM modelling (Booth et al. 2014) and have since been expanded to include 35 bioclimatic variables (Kriticos et al. 2011). Minimum temperature of the coldest quarter, precipitation of the hottest quarter, solar radiation of the driest quarter, and seasonality metrics (i.e. standard deviation or coefficient of variation of monthly mean conditions) are all examples of such bioclimatic variables. While the bioclimatic indices are

commonly used in species distribution models, there are many additional measures (e.g. Huntley et al. 1995; Nitschke & Innes 2008; Pena et al. 2014) that can be derived from climate and weather information. The abundance of climate datasets that represent a range of variables at varying spatial and temporal resolutions, mean that there are an incredibly large number of ecologically meaningful metrics that could potentially be calculated.

A wide range of climate datasets are freely available for ecological modellers to use; however, they are typically impacted by a trade-off between spatial and temporal resolution. While a higher level of precision (i.e. spatial resolution) can be conflated with better accuracy (Daly 2006), the strong relationship between climatic variables and elevation means that increased spatial resolutions may better represent the niche, particularly in regions of complex topography (Guisan et al. 2007; Ashcroft et al. 2009; Dobrowski et al. 2009; Elith & Franklin 2013; Franklin et al. 2013). Australia has several nationally calibrated climate datasets. Two of these, the Australian Water Availability Project dataset (AWAP; Jones et al. 2009; Raupach et al. 2009; Raupach et al. 2012), and the SILO database (Jeffrey et al. 2001) are actively maintained and provide over 100 years of daily surfaces for many variables at a spatial resolution of approximately 5 km (at the equator, given a resolution of 0.05°). The eMAST dataset (e.g. Whitley et al. 2014; Xu et al. 2015) contains data for a range of climate variables at monthly and further aggregated temporal resolutions, including bioclimatic indices, at a spatial resolution of approximately 1 km, but is limited to the period between 1970 and 2012. The software package ANUCLIM (Hutchinson & Xu 2011) provides users with a range of tools for producing customised climate datasets for Australia in addition to a series of supporting algorithms such as BIOCLIM. Global datasets cover a much broader extent and are much more heavily impacted by the trade-off between spatial and temporal resolution in comparison to national Australian products.

The original WorldClim dataset (Hijmans et al. 2005) currently has over 15,000 citations and is one of the most widely used climate datasets in ecology. WorldClim was interpolated using global weather station observations with high-precision (approx. 1 km grid cells) coverage across the globe, and therefore is often an attractive option in comparison to low-precision alternatives. This dataset has since been updated to use additional supporting surfaces (i.e. coastal proximity, remote sensing data) and include wind speed, humidity and solar radiation as additional variables (Fick & Hijmans 2017). While both WorldClim datasets are of a high spatial resolution, they represent long term mean conditions between 1950 and

2000. This means that temporal variability may only be assessed in terms of seasonality (i.e. variation across different months of the year). Furthermore, the global coverage necessitates the use of weather station observations that can vary considerably in their spatial density and comprise a temporal mosaic of records that do not always overlap. Nevertheless, WorldClim has been widely adopted in species distribution modelling applications (Elith & Franklin 2013; Booth et al. 2014) and has been used as a set of base surfaces creating blended climatologies (e.g. CliMond; Kriticos et al. 2011) and time-varying datasets (e.g. TerraClim; Abatzoglou et al. 2018) for ecological modelling applications. Additional datasets such as MERRAClim (Vega et al. 2017) and CHELSEA (Karger et al. 2017) have also emerged in recent years that downscale coarse-scaled global climate reanalysis products (i.e. climate models blended with observational data; Berrisford et al. 2009; Rienecker et al. 2011; Schneider et al. 2014) using statistical and empirical techniques.

1.3. RESEARCH GAPS AND PROJECT AIMS

Climate interpolation techniques have remained relatively unchanged in Australia over the past two decades (e.g. Hutchinson 1998; Jeffrey et al. 2001; Jones et al. 2009; Stewart & Nitschke 2017). These methods usually rely upon latitude, longitude and elevation to interpolate weather station observations, despite the known influence of mesoscale climate drivers that can be inferred using terrain attributes (Daly et al. 2007; Daly et al. 2009; Ashcroft & Gollan 2012) and remote sensing data (Wan et al. 2015). At the commencement of this research, few studies had directly incorporated thermal remote sensing data into interpolated climate surfaces (Hengl et al. 2012). The maturity of remote sensing products derived from Moderate Resolution Imaging Spectroradiometer (MODIS) observations provides a valuable opportunity to improve interpolated climate datasets. As remote sensing data provides a broad spatial coverage, it can potentially minimise error and biases that are associated with observation density and different land cover types.

Correlative species distribution modelling studies have only rarely attempted to incorporate inter-annual variability in climate or weather for prediction. Of those studies that have, almost all have been focused on mobile species such as birds (Reside et al. 2010) and mammals (Bateman et al. 2012; but see Zimmerman et al. 2009). The popular WorldClim datasets represent monthly mean conditions and therefore the temporal signal in the data is

limited to seasonality (i.e. the long term mean intra-annual variability). Time-series climate datasets that have enough spatial precision to describe fine-scale environmental gradients in topographically complex landscapes are rare, and therefore data availability presents a considerable challenge for such analyses. The temporal distribution of climate may describe an important component of the niche that is otherwise neglected when relying on long term means to characterise environmental conditions.

The increasing availability of climate datasets presents both a challenge and an opportunity for ecological modelling. New datasets may better represent the physical processes that drive climate and potentially lead to better predictions; however, it may not be clear which dataset is best to use. These datasets all represent models that are subject to their own strengths and weaknesses. An example of the potential disparity between climate datasets is illustrated in Figure 1.1. Precipitation surfaces result in a smoothed surface when applying convolution filters to the supporting digital elevation model prior to interpolation (250 m interpolation in Chapter 4 and Fedrigo et al. 2019; eMAST). Both WorldClim datasets neglect to account for the well-known lack of strong correlation between elevation and precipitation at scales below 5 to 10 km (Hutchinson 1998, Sharples et al. 2005, Stewart et al. 2017/Chapter 3) that results in unrealistically precise surfaces. AWAP is interpolated across a coarse DEM using observational data, and the Climate Hazards group Infrared Precipitation with Stations (CHIRPS; Funk et al. 2015) blends station records with remote sensing data.

Comparative analyses of disparate climate datasets for species distribution modelling remain rare. Understanding how dataset selection may impact species distribution models is critical, especially if extrapolating to climate change scenarios where the embedded biases may be amplified (Baker et al. 2016). The diverse range of climate datasets that are now available have been generated with a mosaic of methods, observations, and supporting datasets which means that a controlled comparison of their performance in secondary modelling applications is limited.

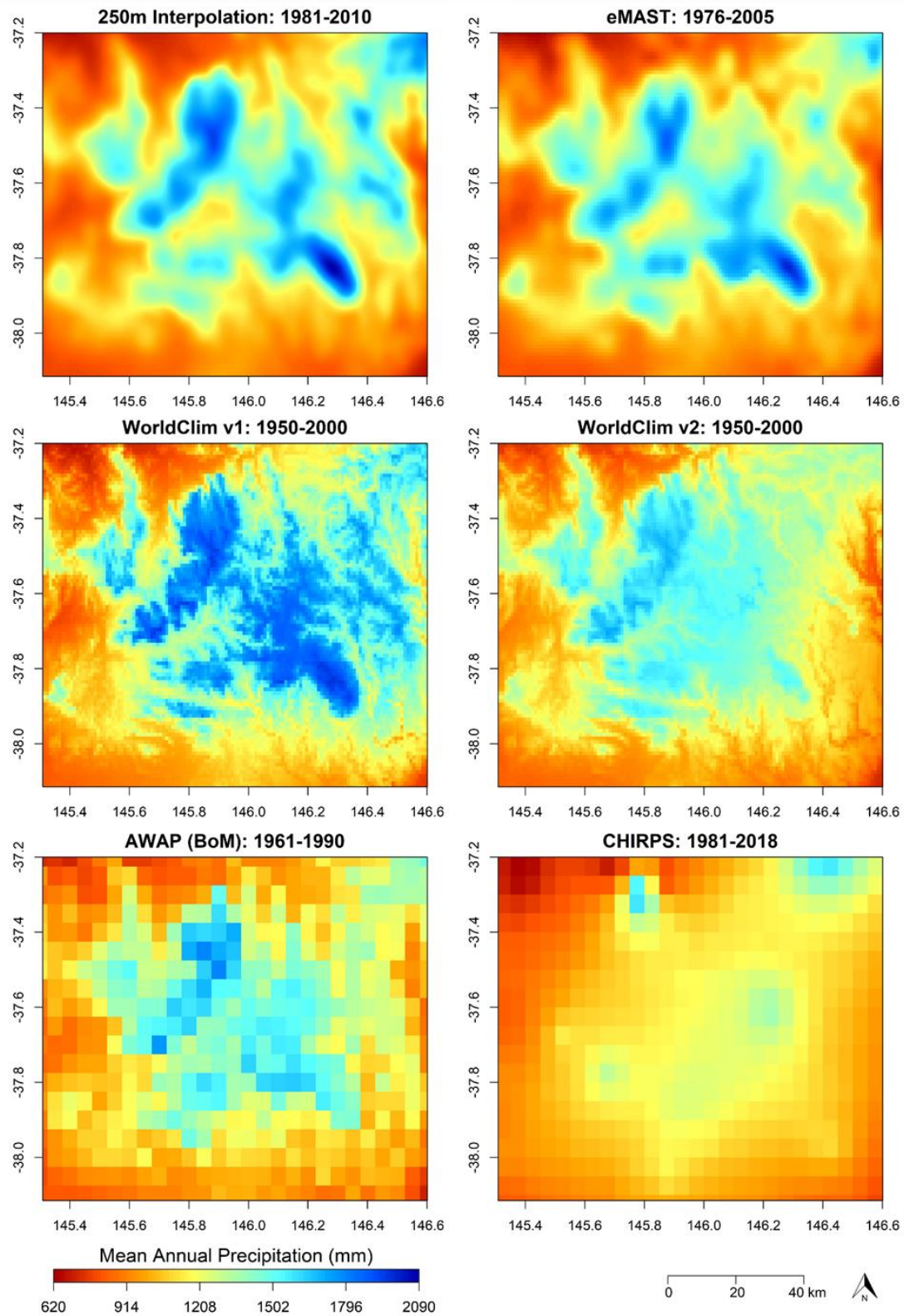


Figure 1.1: Gridded mean annual precipitation data for the central highlands region of Victoria, derived from interpolations developed as part of Chapter 4 (250 m interpolation), the eMAST dataset (Xu et al. 2015), WorldClim (Hijmans et al. 2005; Fick & Hijmans 2017), the Australian Water Availability Project (Jones et al. 2009; Raupach et al. 2009; Raupach et al. 2012) and CHIRPS (Funk et al. 2015).

Given the research gaps identified, the aims of this research are to:

1. Examine the effectiveness of emergent techniques for interpolating climate variables at ecologically relevant scales
2. Investigate the temporal characteristics of climate and how this influences the predicted distribution of sessile organisms
3. Assess the importance of climate dataset selection for correlative species distribution models

1.4. RESEARCH QUESTIONS

This thesis will address the aims listed in the previous section by asking the following research questions:

1. What potential methods are likely to improve climate interpolation performance, and how do they compare against existing techniques?
 - a. How do geostatistical methods perform relative to thin plate splines for interpolating temperature in southeast Australia?
 - b. How do secondary prediction surfaces such as thermal remote sensing data and indices derived from local topography impact temperature interpolation performance, and what is the magnitude of difference between competing techniques?
 - c. Can these methods be applied reliably in novel environments that differ substantially from the temperate climate of southeast Australia?
 - d. What are the key differences between regional interpolations using these emergent techniques and contemporary datasets?
2. What is the importance of interannual variability in climate for modelling the distribution of sessile organisms?
 - a. How can multi-decadal climate datasets be used to generate ecologically relevant variables that summarise interannual variability?

- b. What is the impact of covariates that characterise interannual variability in climate on the statistical performance and spatial configuration of predicted plant species distributions?
 - c. Does accounting for the asymmetrical distribution of climate extremes lead to better predictions of plant species distributions?
- 3. How important is selecting a suitable climate dataset for correlative species distribution modelling?
 - a. Do regional interpolations lead to better modelling outcomes than global datasets?
 - b. Do emerging climate interpolation techniques perform better than long-established methods when modelling species distributions?
 - c. What is the relationship between the statistical performance of climate interpolations and the predictive performance of species distribution models?
 - d. What is the potential for alternate climate datasets to complement one another in multi-model ensembles when predicting species distributions?
 - e. How can spatially continuous measures of congruence and uncertainty support the interpretation of multi-model ensembles?

1.5. STUDY OVERVIEW AND OBJECTIVES

The aims and research questions listed above will be addressed throughout four analysis chapters following the conceptual framework illustrated in Figure 1.2. The first two of these chapters (2 and 3) evaluate climate interpolation methods and the outputs include a series of temperature datasets used for subsequent analyses. Precipitation, vapour pressure and Penman-Monteith reference evapotranspiration (Allen et al. 1998) datasets were generated and described as part of subsequent supplementary materials or as contributions to a predictive ecosystem mapping study (Fedrigo et al. 2019). Solar radiation and wind speed were obtained from external sources (Raupach et al. 2009; Raupach et al. 2012; McVicar 2011). The final two analysis chapters (4 and 5) explore the impacts of temporal variability in climate and dataset selection on the predicted distribution of plant species in Victoria using systematically sampled presence-absence data.

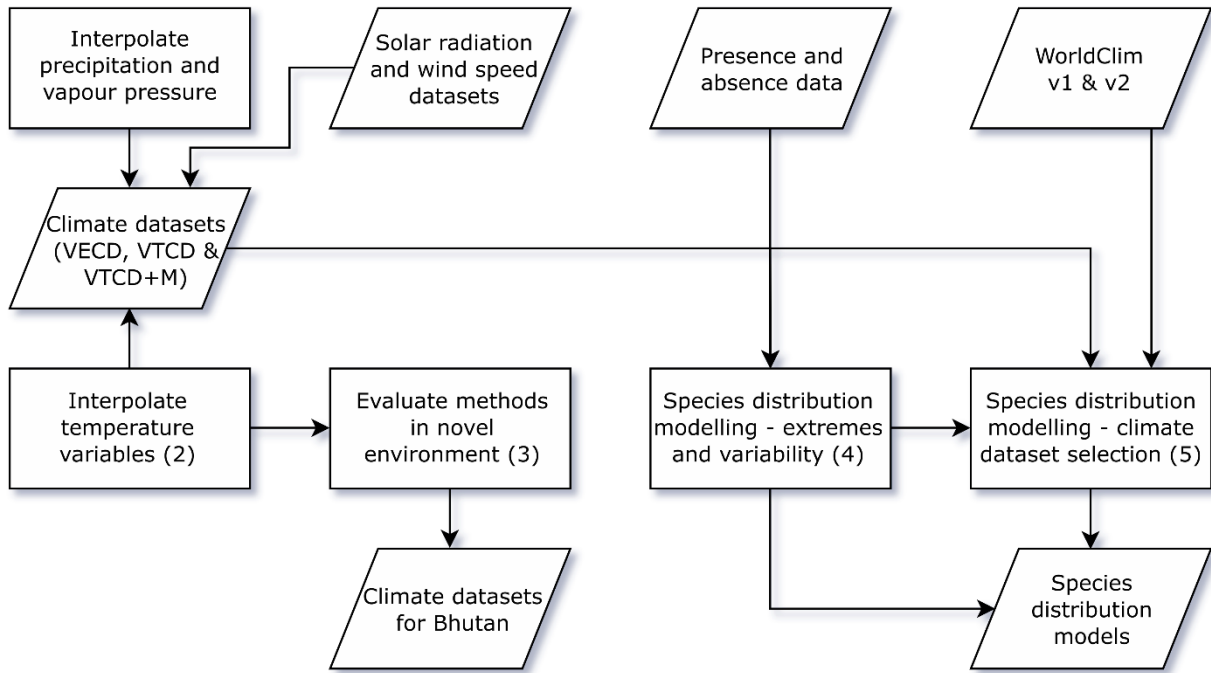


Figure 1.2: Conceptual framework followed to address each of the research objectives. Each of the individual analysis chapters are indicated in parenthesis (2 to 5).

The first analysis chapter explores the potential for improving temperature interpolation using thermal remote sensing data and local topographic indices generated from a digital elevation model of Victoria. An early version of this manuscript included precipitation; however, it was relocated to supplementary materials for separate studies (i.e. Chapter 4, and Fedrigo et al. 2019) to focus directly on temperature, that is an essential variable for deriving secondary datasets such as vapour pressure deficit and potential evapotranspiration. The analysis includes a comparison of geostatistical and spline-based interpolation methods in conjunction with additional covariates that assist in explaining the spatial distribution of mesoscale processes (e.g. cold air drainage and pooling) and microclimatic conditions driven by land cover. The methodological framework (Figure 1.3) seeks to address the objectives listed below.

1. To compare the performance of interpolated temperature datasets calibrated using commonly applied methods (e.g. full spline dependence on latitude, longitude and elevation) with those that use thermal remote sensing data and local topographic indices as linear covariates.
2. To compare the performance of geostatistical and spline-based methods for interpolating temperature when using the methods described in point 1.

3. To generate multi-decadal (1981-2014) climate datasets at high spatial (approx. 250 m) and a range of temporal (daily, monthly, monthly mean) resolutions for Victoria, southeast Australia.
4. To describe the behaviour of the datasets described in point 3 relative to national and global climate across regions of complex topography.
5. To enable comparisons of climate surfaces in secondary applications (e.g. species distribution modelling) by generating each of the datasets listed in point 3 using consistent inputs (i.e. weather stations used, observation values and DEM).

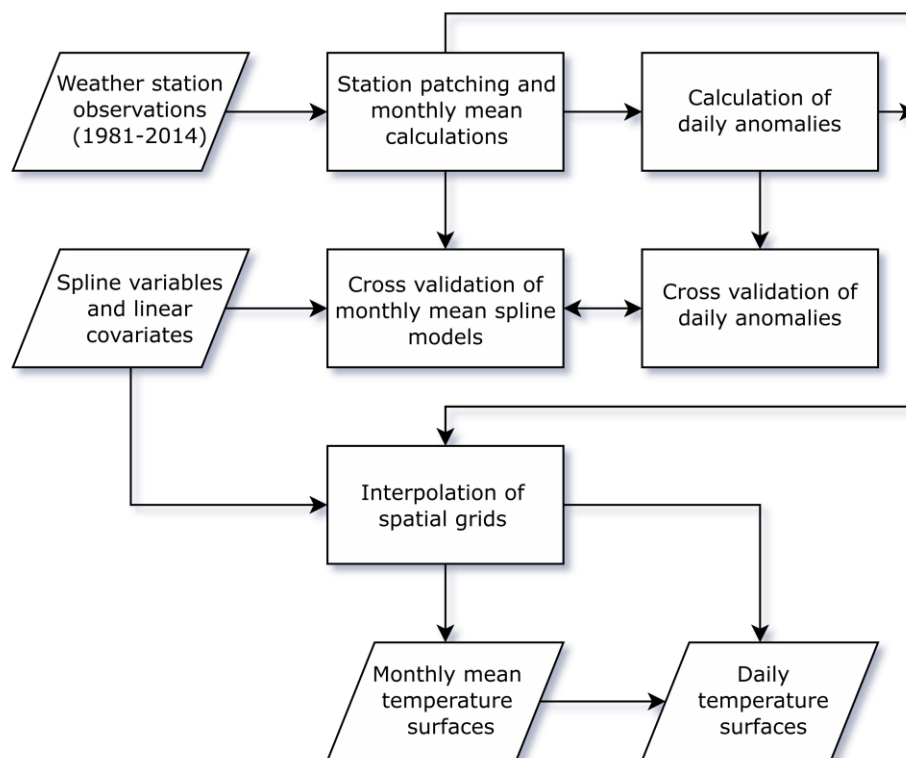


Figure 1.3: Methodological framework and overview for Chapter 2 (*‘Improving temperature interpolation in southeast Australia’*).

The transferability of emerging temperature interpolation methods was evaluated in the second analysis chapter, where the same techniques used in southeast Australia were applied in the Royal Himalayan Kingdom of Bhutan. In addition to temperature, vapour pressure and precipitation interpolation methods were also evaluated. The national weather station observations used in this chapter have not previously been included in global climate datasets, which provided an opportunity to also investigate the potential influence of observation density and associated biases that may arise in under sampled, topographically extreme landscapes.

Monthly mean precipitation, vapour pressure, and temperature datasets were generated to make full use of the local weather station observations and to create a new national data resource for Bhutan. The methodological framework (Figure 1.4) seeks to address the objectives listed below.

1. To evaluate the performance of temperature, vapour pressure and precipitation interpolation techniques in a topographically extreme landscape.
2. To demonstrate the potential for improving temperature interpolation performance when using thermal remote sensing data and topographic indices as spline covariates in Bhutan.
3. To compare the relative differences in temperature interpolation performance between the monsoonal climate of Bhutan and the temperate climate of southeast Australia.
4. To generate a series of monthly mean (1986-2015) temperature, vapour pressure and precipitation datasets for Bhutan.
5. To compare global datasets with those described in point 2 that were calibrated using the local weather station network.

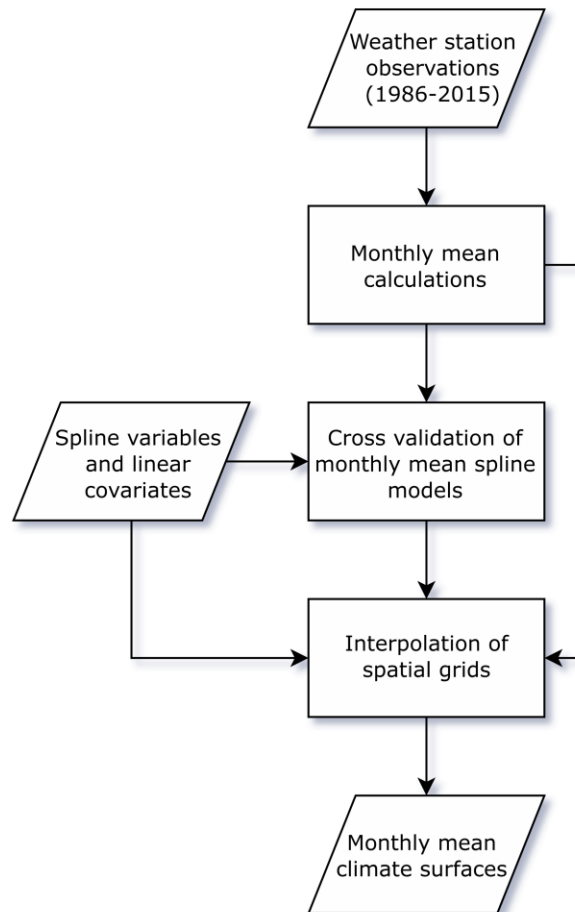


Figure 1.4: Methodological framework and overview for Chapter 3 (*‘Assessing the transferability of emerging interpolation techniques’*).

The third analysis chapter explores the temporal characteristics of climate and how it influences the predicted distribution of plant species. Monthly mean bioclimatic variables represent long term conditions, and therefore datasets such as WorldClim (Hijmans et al. 2005; Fick & Hijmans 2017) can only represent seasonality and not interannual variability. Studies evaluating the impact of interannual climate variability on correlative distribution models for plant species remain extremely rare. The time series datasets developed for Victoria were used to characterise these interannual trends at fine spatial scales relative to contemporary alternatives in the region. Responses to the magnitude and expected frequency of climate extremes were assessed for 37 plant species across Victoria. The methodological framework (Figure 1.5) seeks to address the objectives listed below.

1. To identify and generate a series of climate extreme variables that can summarise the magnitude and frequency of climate extremes across multi-decadal timescales.

2. To assess the statistical performance and spatial response of species distributions predicted using typical climate extremes with those that also consider the coldest winters, and the hottest and driest summers.
3. To evaluate alternate isotropic and asymmetric measures of variability derived from GEV distributions and assess their ability to improve predicted species distributions.

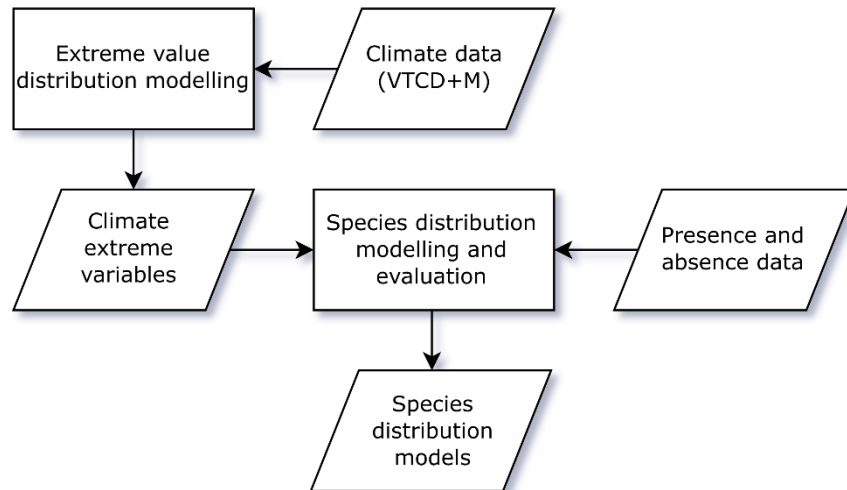


Figure 1.5: Methodological framework and overview for Chapter 4 (*‘Evaluating temporal variability in climate for predicting plant species distributions’*).

The fourth and final analysis chapter investigates the importance of climate dataset selection for modelling species distributions. The proliferation of global climate datasets in recent years means that there are many to choose from when building ecological models, yet comparisons of their predictive performance remains rare. The climate datasets generated for Victoria were used to compare distribution models fitted for each of the 37 plant species selected previously for the analysis of extremes. The original and updated WorldClim datasets were included in the analysis to provide a comparison of regional and global datasets that are interpolated with traditional methods or supported by secondary variables such as remote sensing data. Note that while the CHIRPS dataset provides remotely sensed precipitation surfaces, it poorly represents rainfall regimes in southeast Australia and was not included in this research. Multi-model ensembles were also evaluated against individual models to explore the potential for additive improvements that may be achieved using alternate datasets. The methodological framework (Figure 1.6) seeks to address the objectives listed below.

1. To compare the performance of predicted species distributions when modelled using regionally calibrated and global climate datasets.
2. To evaluate the performance of predicted species distributions when modelled using emerging climate datasets that are supported using thermal remote sensing data and local topographic indices, in comparison to long-established methods (i.e. full spline dependence on latitude, longitude and elevation).
3. To assess the performance and of multi-model ensembles relative to individual models when predicting species distributions with alternate climate datasets.
4. To develop metrics that can support the interpretation of species distributions predicted with multi-model ensembles.

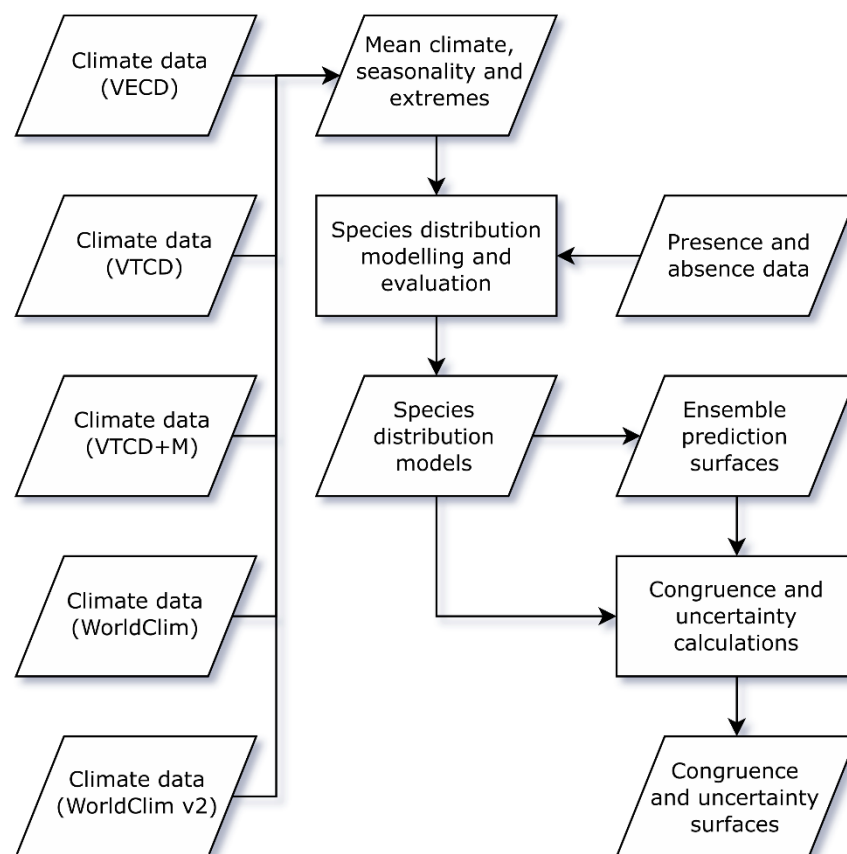


Figure 1.6: Methodological framework and overview for Chapter 5 (*Evaluating disparate climate datasets for predicting plant species distributions*). High resolution datasets developed specifically for this thesis include the Victoria elevation-only climate dataset (VECD), the Victorian topo-climate dataset (VTCD) and the Victorian topo-climate plus MODIS dataset (VTCD+M).

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2

CHAPTER TWO: IMPROVING TEMPERATURE INTERPOLATION IN SOUTHEAST AUSTRALIA¹

This chapter explores the potential for improving temperature interpolation using thermal remote sensing data and local topographic indices generated from a digital elevation model of Victoria. The analysis includes a comparison of geostatistical and spline-based interpolation methods in conjunction with additional covariates that assist in explaining the spatial distribution of mesoscale processes (e.g. cold air drainage and pooling) and microclimatic conditions driven by land cover. The results inform the development and selection of the temperature datasets used for species distribution modelling in subsequent chapters.

2.1. INTRODUCTION

Interpolated climate datasets are a core component in a broad range of applications, from fire modelling and calculation of drought indices, to ecological assessments, species distribution modelling and agricultural assessments. Gridded climate datasets utilising macroscale elevational gradients are readily available at global and continental scales (Jeffrey et al. 2001; Hijmans et al. 2005; Haylock et al. 2008; Hutchinson et al. 2009; Jones et al. 2009). Bioclimatic variables such as mean annual temperature and precipitation, annual diurnal range and maximum temperature of the driest quarter have been heavily utilised in species distribution modelling and ecological assessments since the 1980s (Booth 1985; Nix & Busby 1986; Elith & Franklin 2013). Over 20% of Eucalypt species persist in regions that vary by less than 1 °C in mean annual temperature (Hughes et al. 1996), which highlights the importance

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of using high quality climate data for ecological studies. The calibration and spatial resolution of prediction surfaces, however, may mask the effect of topographic complexity on climate and lead to the homogenisation of spatial variability across landscapes. This homogenisation may have implications for species distribution modelling, which can require fine scale characterisation of climatic variables to reliably represent the fundamental or realised niche of a species (Kearney et al. 2010). Spatial homogenisation may also restrict the predictability of climatic refugia that can allow organisms to persist in regions that would otherwise be unexpected (Ashcroft et al. 2012). Climatic refugia tend to exist within heterogeneous landscapes with diverse topographic and edaphic conditions (Kirkpatrick & Fowler 1998; Burke 2002). Riparian corridors, for example, have acted as refugia for mesic species during droughts and fires associated with past climatic events (Aide & Rivera 1998; Rouget et al. 2003).

Gridded climate data are commonly interpolated using point locations (Hutchinson 1995; Jeffrey et al. 2001; Hijmans et al. 2005; Hutchinson et al. 2009; Jones et al. 2009) or generated by downscaling coarse data using methods such as those described by Wang et al. (2012; 2016) that apply elevational lapse rates against a high resolution digital elevation model (DEM). Many alternate methods exist for interpolating climate data, including kriging, thin plate splines, regional regressions and process-based microclimate models.

The kriging system of linear equations for geostatistical interpolation is covered in detail by Cressie (1993), Hengl (2009) and Bivand et al. (2013). The value at an unknown location is calculated by the weighted sum of the surrounding observations. These weights are determined by solving the kriging system, which requires the covariance structure of the observations to be modelled prior to interpolation. The covariance function is represented through the variogram; a valid positive-definite model (i.e. linear, spherical, exponential, etc.) fit through semivariance values calculated for binned observations at increasing lag distances. The choice of variogram model is a non-trivial process that requires consideration beyond minimising the sum of squares (Cressie 1989; Cressie & Zimmerman 1992). For example, a Gaussian variogram model exhibits parabolic behaviour near the origin and can lead to instability in the kriging system where there are large differences that occur between values at short ranges. Furthermore, a poorly defined autocorrelation structure may result in a variogram with insufficient range, leading to spatial artefacts (i.e. ‘bullseye’ patterns) and defaulting to the mean in regions where observations are too distant from the prediction location. Kriging

has been directly compared against spline interpolation in several studies (Hutchinson & Gessler 1994; Laslett 1994; Boer et al. 2001; Hofstra et al. 2008); however, the performance of any given interpolation method is heavily dependent upon the availability of suitable and representative sample data (Isaaks & Srivastava 1989; Li & Heap 2014).

Thin plate splines (Wahba 1990; Hutchinson 1995) are commonly used for geospatial interpolation of climate. The thin plate spline model consists of two main components; an affine component which fits the global trend as a function of spline variables (latitude and longitude for bivariate splines; latitude, longitude and elevation for trivariate splines), and a local non-affine component that adjusts the local non-linear surface. These components are fit to minimise the total amount of bending energy that is required to fit the spline surface. The regularisation parameter allows for inexact interpolation by dictating the degree of smoothness in the spline surface and is commonly estimated using generalised cross-validation (GCV; Craven & Wahba 1979; Hutchinson & Xu 2013). Partial thin plate splines also include a parametric regression component (Bates et al. 1987) to incorporate additional independent covariates. Splines are commonly used for generating climate data as they are smooth interpolators (Hutchinson & Gessler 1994), can be readily automated as no initial analysis of spatial dependence is required, and are easily implemented given the availability of robust, purpose built software such as ANUSPLIN (Hutchinson & Xu 2013) and ANUCLIM (Hutchinson & Xu 2011). Trivariate splines are often preferred for climatological analyses as they allow for a spatially varying dependence upon elevation (Hutchinson 1995; Hutchinson et al. 2009). Spline based interpolation methods have been used to generate global and continental scale climate datasets; however, these datasets often involve a trade-off between spatial and temporal resolution.

The SILO (Jeffrey et al. 2001) and Australian Water Availability Project (AWAP; Jones et al. 2009) datasets use spline-based methods for interpolating climate variables (with the exception of SILO precipitation which uses ordinary kriging for precipitation) across Australia at daily, monthly and further aggregated temporal resolutions. Both provide daily data at a spatial resolution of approximately 5 km² across Australia, with long term provisional climate normals (monthly aggregated observations having sufficient number of observations to represent the 30 year normal period) available at a slightly higher resolution of approximately 2.5 km² in the AWAP dataset. Climate observations are interpolated directly based on the target temporal resolution in the SILO dataset. The AWAP dataset utilises the anomaly approach,

whereby provisional climate normals (hereafter referred to as climate normals) and climate anomalies (deviation from mean conditions) are interpolated separately and combined to form the final prediction surfaces. The anomaly approach employed by the AWAP method was reported to improve cross-validation error statistics by approximately 40% in comparison to the direct approach (Jones et al. 2009), which supports earlier recommendations to interpolate anomalies rather than raw observation data (Jones & Hulme 1996).

WorldClim surfaces were developed using trivariate splines to provide a high spatial resolution (approx. 860 m²) and globally consistent database of monthly mean temperature and precipitation values for 1950 to 2000 (Hijmans et al. 2005). Globally representative climate datasets prior to this study were relatively coarse in spatial resolution, ranging from 18.5 km² (New et al. 2002) to 55.6 km² (Leemans & Cramer 1991; Mitchell & Jones 2005) at the equator. The CliMond database (Kriticos et al. 2012) combines WorldClim and CRU data (New et al. 1999; New et al. 2002) to generate monthly climate surfaces that allow for temporal variation in these base surfaces. The WorldClim dataset and derived bioclimatic variables have been heavily used in correlative species distribution models (Leathwick & Austin 2001; Elith & Franklin 2013; Kuttywayo et al. 2013; Guo et al. 2015; Gelviz-Gelvez et al. 2015) due to their relatively high resolution and global consistency.

Kriging based climate analyses have been investigated more commonly in Europe (Dobesch et al. 2007; Ly et al. 2011). Hofstra et al. (2008) demonstrated that kriging with a global variogram fit and an external drift component performed better on average than five alternative methods (including spline based methods) when interpolating climate variables across the United Kingdom. The E-OBS dataset (Haylock et al. 2008), however, is calibrated based on European climate normals interpolated using trivariate splines. Hengl et al. (2012) investigated the potential for spatio-temporal regression kriging of daily temperature in Croatia using a time series of Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) mosaics. While limited somewhat by the 8-day temporal resolution of the composite MOD11A2 product (in order to minimise the effect of missing data), the final surfaces generated incorporate microclimatic factors driven by land use, such as the urban heat island effect and forest cover, which cannot be detected using topographical data alone.

In North America, the PRISM model (Daly et al. 2002) provides a statistical framework for incorporating expert knowledge into climate mapping. The effect of orography on

precipitation, elevation gradients, atmospheric interactions, and coastal distance are all modelled within the PRISM framework. The ClimateWNA and ClimateAP models (Wang et al. 2012; Wang et al. 2016) are used to downscale pre-existing climate datasets (such as those generated by PRISM and WorldClim) using a combination of bilinear interpolation and elevational lapse rates. This downscaling allows for the generation of climate data at spatial resolutions limited only by the fidelity of the input DEM. This approach is limited given that macroscale elevational gradients used to generate coarse resolution climate data cannot effectively account for mesoscale processes such as cold air drainage due to the scale of the initial interpolated surface. Alternatively, software packages such as ANUSPLIN (Hutchinson & Xu 2013) and ANUCLIM (Hutchinson & Xu 2011) can be used to generate climate data at spatial grain only limited by the resolution of the input DEM.

Regional regression and processed based modelling techniques can also be used to generate very high fidelity climate datasets of varying spatial and temporal resolution. Regional regression models that incorporate the additional drivers of climate such as slope, aspect, and vegetation cover, however, require extensive field based campaigns to capture highly variable *in-situ* conditions (e.g. across multiple forest types, shade classes, slopes, aspects) that would not otherwise be possible using the historical network of standardised weather stations (Ashcroft & Gollan 2012; Hardwick et al. 2015). Process-based equations such as those implemented by MT-CLIM can be used to downscale coarse resolution climate data or interpolate point observations by applying elevational lapse rates, correcting for the ratio of solar radiation on a sloped surface to that of a flat surface and adjusting for the effects of vegetation cover (Running et al. 1987; Moore et al. 1993; Nyman et al. 2014). Process-based models, such as Niche Mapper, are also able to disaggregate daily data into hourly predictions using a broad range of climatic drivers as input variables; however, these models do not correct for mesoscale processes such as cold air drainage (Kearney et al. 2014).

Opportunities exist to improve temperature interpolation by incorporating local topography and remotely sensed land surface temperature data into prediction surfaces. The MODIS LST algorithm and workflow for the 8-day composite product (MOD11A2) includes atmospheric correction, cloud masking, quality control and correction factors for quarterly land use (MOD12Q1) and daily snow cover (MOD10_L2; Snyder & Wan 1998; Wan 2006), which facilitates use in such studies. A significant advantage of this remote sensing data is the ability to quantify the thermal properties of heterogeneous landscapes at broad spatial scales.

Topographic indices have also proven effective in improving minimum temperature interpolation performance using historical weather station networks (Daly et al. 2007; Daly et al. 2009) and field based temperature loggers (Ashcroft & Gollan 2012). The use of localised topography based metrics allows for local cold air drainage regimes, where cool dense air from higher elevation flows downslope and pools in topographic depressions overnight, to be quantified. Studies using topographic metrics for interpolation have focused on relatively coarse (4 km) or very fine (25 m) resolution topography. Additional testing at fine to intermediate scales using historical weather station networks is required to further explore the utility of these metrics.

This research assesses multiple interpolation methods using predictor variables that are compatible with the existing historical weather station network to provide novel temperature datasets for Victoria, south east Australia. Interpolating temperature surfaces at high resolution provides opportunities to capture the effects of mesoscale processes that may not otherwise be possible at coarser resolutions or via downscaling approaches. The use of the existing long term climate observation record and anomaly interpolation also allows for the generation of daily surfaces at broad temporal scales. The objective of this research is to assess the relative improvement in temperature surfaces that can be achieved by incorporating thermal remote sensing data and localised topography as independent covariates, and to identify the optimal interpolation algorithm for including these predictors. Daily climate data is required for many applications, and accounting for mesoscale processes will assist in bridging the gap between statistical interpolation routines and process-based models without the need for additional post-processing.

2.2. METHOD

2.2.1. STUDY EXTENT

The state of Victoria is located in south east Australia (141 – 150° E, 34 – 39° S) with a total land surface area of 227,416 km² that ranges between 0 m and 1980 m in elevation above sea level. Topography becomes increasingly variable in the north eastern region of the state due to the location of the Australian Alps (Figure 2.1). Throughout the study period (January 1981 – August 2014) there were 140 weather stations recording temperature across Victoria, with a mean minimum separation distance of 18.7 km.

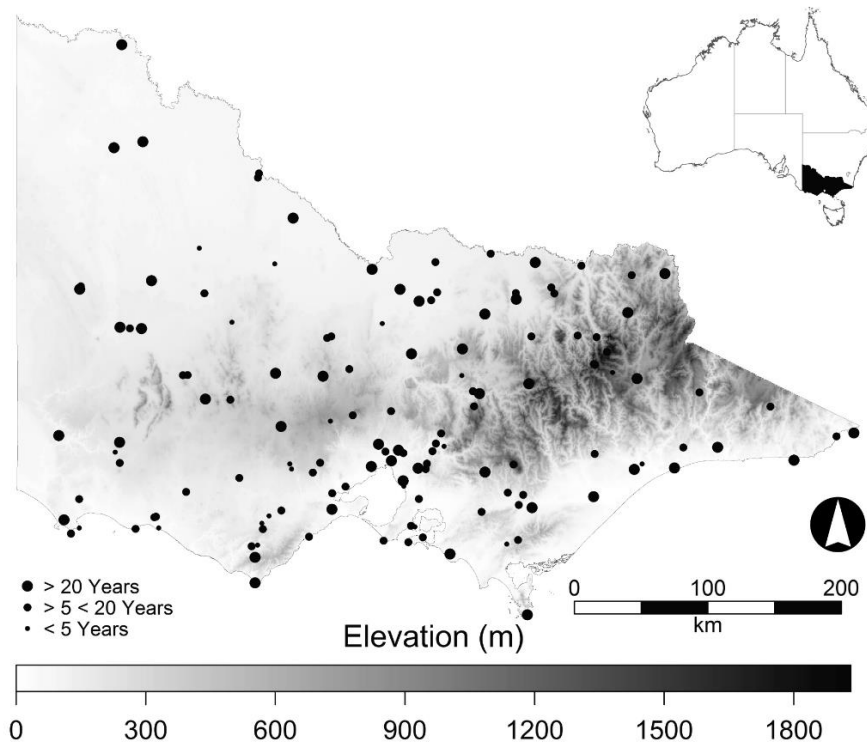


Figure 2.1: Digital elevation model of Victoria, Australia (Fenner School of Environment and Society and Geoscience Australia, 2008) and the network of temperature observations recorded between January 1981 and August 2014.

2.2.2. DATASETS

Daily temperature records between January 1981 and August 2014, obtained from the SILO Patched Point Dataset (Jeffrey et al. 2001), were used in the study. All interpolated observations were removed prior to analysis. Latitude, longitude and elevation were acquired directly from weather station metadata provided with the SILO Patched Point Dataset for maximum and minimum temperature. Temperature prediction surfaces were calculated using the GEODATA 9 Second (approx. 250 m cell resolution) Digital Elevation Model (DEM) Version 3 (Fenner School of Environment and Society & Geoscience Australia 2008).

A localised topographic index was used to test for the effects of fine scale topographic complexity that drive temperature inversions due to cold air drainage regimes. The topographic index was used for modelling minimum temperatures but not for maximum temperatures due to coefficient instability between months and the limited effects of cold air drainage on summer maximum temperatures (Daly 2006). This index was calculated as the difference between

elevation at each DEM cell and the focal minimum (Daly et al. 2007; Daly et al. 2009; Ashcroft & Gollan 2012). To determine the optimal focal range, a series of search diameters between 750 m and 4.25 km were assessed using regression analysis. A search diameter of 1.25 km was selected to maximise the amount of variance explained while ensuring a sufficient number of cells were used in the analysis. A square root transform was applied to the topographic index to improve normality of model residuals and to limit the number of extremes in prediction surfaces caused by large but infrequent elevational gradients present across the landscape.

Remotely sensed MODIS LST data acquired between March 2000 and December 2010 were used to construct standardised monthly surfaces for day time and night time land surface temperature (LST). Australia-wide composite mosaics of the MOD11A2 8-day LST collection 5 product (approx. 1 km² cell resolution; LP DAAC 2014, Paget & King 2008) were obtained from the AusCover Remote Sensing Data Facility (www.auscover.org.au) and subset to the extent of Victoria. Daily MODIS-LST images were frequently missing large amounts of data due to cloud cover, atmospheric conditions and quality control processes, therefore the 8-day composites were used to maximise the number of available data points for creating standardised surfaces. Composite images where more than 30% of cells contained no data were excluded from all subsequent analyses. Each composite image was standardised as:

$$MODIS_{STD,i} = (\bar{x}_i - x_{i,j})/\sigma_i$$

where $\bar{x}_i$ and σ_i are the mean and standard deviation of image i , and $x_{i,j}$ is the LST value assigned at cell location j . The final standardised surfaces were generated by grouping images by month, removing outliers by excluding values falling outside of the 95% confidence interval at each cell location, and calculating the mean value at each cell location.

A number of predictor variables were excluded from the study, despite their common inclusion in correlative and mechanistic climate analyses. Distance to the coast (Daly et al. 2007) was excluded due to a high correlation ($r = 0.93$) with latitude and the use of standardised meteorological weather stations precluded the use of vegetation cover, slope, aspect and their interactions (Ashcroft & Gollan 2012; Kearney et al. 2014). Solar radiation metrics (direct and diffuse solar radiation, modelled ratio of solar radiation on a sloped surface to that of a flat surface accounting for terrain-dependent shading; Moore et al. 1993; Böhner & Antoni c 2009; Nyman et al. 2014) were initially considered as predictor variables; however, model coefficients demonstrated sign inconsistencies in several months, leading to their exclusion.

2.2.3. DATA ANALYSIS

Predictions of daily maximum and minimum temperatures were obtained by interpolating anomalies derived from monthly climate normals in one 30 year reference period; 1981 –2010. Climate normals were interpolated using partial bivariate splines (2DS), full and partial trivariate splines (3DS) and regression kriging (RK; Odeh et al. 1995).

All kriging based analyses were performed in R (R Core Team 2016) using the *gstat* package (Pebesma 2004) and all spline-based analyses were performed with ANUSPLIN version 4.4 (Hutchinson & Xu 2013). RK was implemented by first fitting regression models to the data points followed by ordinary kriging of model residuals. The final predictions at each location were calculated as the sum of the modelled value and the interpolated residual. Regression models were fit by generalised least squares using the *nlme* (Pinheiro et al. 2015) package in R.

The smoothing parameter for spline interpolation was estimated by generalised cross-validation using ANUSPLIN version 4.4 (Hutchinson & Xu 2013). A semi-automated procedure for fitting variograms was used in all kriging analyses. Empirical variograms of regression residuals were calculated and initially fit to models using the *automap* package in R (Hiemstra et al. 2009). The automated fitting procedure optimises variogram model parameters to minimise the residual sum of squares. The Gaussian, exponential, spherical and linear variogram models were all considered throughout the automated fitting procedure. The reliability of each variogram model was then assessed visually. In a small number of cases the fitting procedure was heavily influenced by semivariance in the initial distance bins, resulting in variograms with very short ranges. The parameters of these models were adjusted to provide a more consistent fit to the full empirical variogram.

Climate normals and daily anomalies were cross-validated by iteratively removing one observation from the available data points and using it as a test location. Leave one out cross-validation was chosen to ensure the most accurate representation of location-specific bias, and to minimise the effect of excluding novel observations. Climate normal model parameters were reassessed using the training dataset at each cross-validation iteration. Variogram models were

defined globally for each month during climate normal analysis to ensure a consistent and reliable model.

Model performance was assessed using the coefficient of determination (r^2), mean absolute error (MAE), root mean squared error (RMSE), ratio of the RMSE to the standard deviation of the observations (RSR) and mean error (BIAS). The RSR is a standardised model performance metric that is considered very good when < 0.5 and satisfactory when < 0.7 (Moriassi et al. 2007).

2.2.4. CALCULATION AND ANALYSIS OF CLIMATE NORMALS

Monthly climate normals require a sufficient number of observations to ensure a robust estimate of the long term mean; however, the length of available temperature records varies considerably throughout the Victorian weather station network. The inclusion of short term records can introduce biases and limit model performance if they are not representative of the normal period. Record length was extended using linear regression against nearby long term observations to minimise these biases, which has been shown to be effective in optimising model performance for both temperature and precipitation climate normals (Hopkinson et al. 2012).

For each month, weather stations with at least 20 years of daily observations were considered as long term records and used directly to calculate climate normals. These included on average 36% of the weather stations operating between 1981 and 2010. Weather stations with short to medium term records (5 – 20 years) were then regressed separately against the closest 5 weather stations with long term observations. Models were required to reach a significance level of 1% and have at least 4 years of overlapping observations to be considered further. Short to medium term records were then extended using the regression model returning the highest F score. This procedure allowed 85% of the weather stations operating between 1981 and 2010 to be included in the climate normal analysis. Short term records that did not meet the above criteria were only retained for the analysis of daily anomalies.

Climate normals were then interpolated using partial bivariate splines (2DS), full and partial trivariate splines (3DS) and regression kriging (RK). Partial spline models were

computed by including additional variables as independent covariates. All climate normal interpolations were performed using elevation as either an independent covariate (RK and 2DS) or spline variable (3DS). Elevation was expressed in kilometres for trivariate spline models in order to minimise interpolation error (Hutchinson 1995; Hutchinson et al. 2009). Standardised day time MODIS values were included as an independent covariate for maximum temperature. The topographic index of relative elevation and standardised night time MODIS values were included as additional independent covariates for minimum temperature.

2.2.5. CALCULATION AND ANALYSIS OF DAILY TEMPERATURE

Daily predictions of maximum and minimum temperature were calculated by interpolating anomalies derived from the observed daily temperature and the monthly climate normal. Daily anomalies were calculated as:

$$\Delta Z_{m,t} = Z_{m,t} - \mu_m$$

where μ_m is the climate normal in month m , and Z is the observed value in observation period t . All anomalies were interpolated using bivariate splines. Cross-validated daily temperatures were calculated as the sum of the predicted climate normal and the interpolated anomaly.

Interpolation variance at each target location was used to identify erroneous daily observations. Interpolated anomalies falling outside of 3.6 standard deviations of the observed anomaly were identified as suspect data points (Hutchinson & Xu 2013). All suspect data points were excluded during daily cross-validation and interpolation; however, they were retained for the purposes of calculating cross-validation statistics to maintain conservative error estimates.

2.2.6. ANALYSIS OF TEMPERATURE DEPENDENT BIOCLIMATIC VARIABLES

Variables such as mean annual temperature and mean diurnal range (Hijmans et al. 2005) are commonly used in bioclimatic analyses (Elith & Franklin 2013) and were therefore selected to assess the impact of including the topographic index and standardised MODIS values as predictors for temperature variables. Both variables were calculated using four alternate combinations of maximum temperature and minimum temperature models. The Victorian elevation-only climate dataset (VECD) was calculated using elevation as the only

topographic predictor for both maximum temperature and minimum temperature. The Victorian topo-climate dataset (VTCD) builds upon the VECD with the addition of the topographic index as a predictor for minimum temperature. The Victorian elevation plus MODIS climate dataset (VECD+M) and the Victorian topo-climate plus MODIS dataset (VTCD+M) were calculated by including standardised day time MODIS values for maximum temperature and standardised night time MODIS values for minimum temperature as additional predictor variables. Further analysis of model performance was conducted by subtracting VECD values from the VTCD, VECD+M and VTCD+M, and investigating the distribution of residual values.

2.2.7. ANALYSIS OF MODEL BEHAVIOUR ACROSS A TOPOGRAPHICALLY COMPLEX TRANSECT

Model performance in regions of complex topography were investigated further by extracting mean annual temperature, mean annual diurnal range and mean annual minimum temperature along a 7.75 km transect crossing two valleys. AWAP and WorldClim climate normals were also extracted to provide a comparison against the VECD, VTCD, VECD+M and VTCD+M datasets. The range and variability of extracted values were assessed using cross sections and boxplots.

2.3. RESULTS

Cross-validated error statistics for maximum and minimum temperature climate normals (1981–2010) are presented in Table 2.1. Trivariate splines had the lowest cross-validation error for maximum temperature climate normals. Only marginal performance improvements to maximum temperature were obtained with the partial trivariate spline using standardised day time MODIS LST as an independent covariate. Partial bivariate splines with elevation as an independent covariate provided a minor improvement over the full trivariate spline for minimum temperature climate normals. Including the topographic index of relative elevation as a covariate improved minimum temperature RMSE by approximately 17% in comparison to the best performing elevation only model (2DS-E); however, only negligible differences were found between the partial bivariate spline and the partial trivariate spline. Partial trivariate splines provided the best interpolation performance for all minimum

temperature climate normal models when using standardised night time MODIS LST as an independent covariate (34% improvement in RMSE for 3DS-M and 39% improvement in RMSE for 3DS-TM when compared against 2DS-E).

Table 2.1: Spatially and temporally pooled cross-validated error statistics for monthly mean (1981 – 2010) maximum and minimum temperature interpolated using regression kriging (RK), bivariate splines (2DS) and trivariate splines (3DS). Combinations of elevation (E), topographic index (T) and standardised MODIS values (M) used as independent covariates are indicated in the model suffix.

	r^2	MAE	RMSE	RSR	BIAS
Maximum Temperature (°C)					
RK-E	0.99	0.39	0.56	0.10	0.00
RK-EM	0.99	0.40	0.55	0.09	0.00
2DS-E	0.99	0.39	0.53	0.09	-0.01
2DS-EM	0.99	0.38	0.51	0.09	-0.01
3DS	0.99	0.36	0.51	0.09	0.00
3DS-M	0.99	0.35	0.48	0.08	-0.01
Minimum Temperature (°C)					
RK-E	0.92	0.79	1.03	0.28	-0.01
RK-ET	0.95	0.64	0.83	0.22	-0.01
RK-EM	0.96	0.54	0.71	0.19	0.00
RK-ETM	0.97	0.52	0.67	0.18	0.00
2DS-E	0.93	0.74	0.96	0.26	-0.01
2DS-ET	0.95	0.62	0.80	0.22	-0.01
2DS-EM	0.97	0.50	0.66	0.18	-0.01
2DS-ETM	0.97	0.48	0.63	0.17	0.00
3DS	0.93	0.76	0.99	0.27	-0.03
3DS-T	0.95	0.62	0.80	0.22	-0.01
3DS-M	0.97	0.48	0.63	0.17	-0.01
3DS-TM	0.97	0.45	0.59	0.16	0.00

r^2 = coefficient of determination, MAE = mean absolute error, RMSE = root mean square error, RSR = ratio of the RMSE to the standard deviation of the observations, BIAS = mean error.

Empirical variograms of maximum temperature regression residuals (Figure 2.2) were fit using the Gaussian model from October to April and the exponential model from May to August. Including standardised day time MODIS LST in the regression component for maximum temperature climate normals reduced residual variance, particularly in the warmer months (October to March).

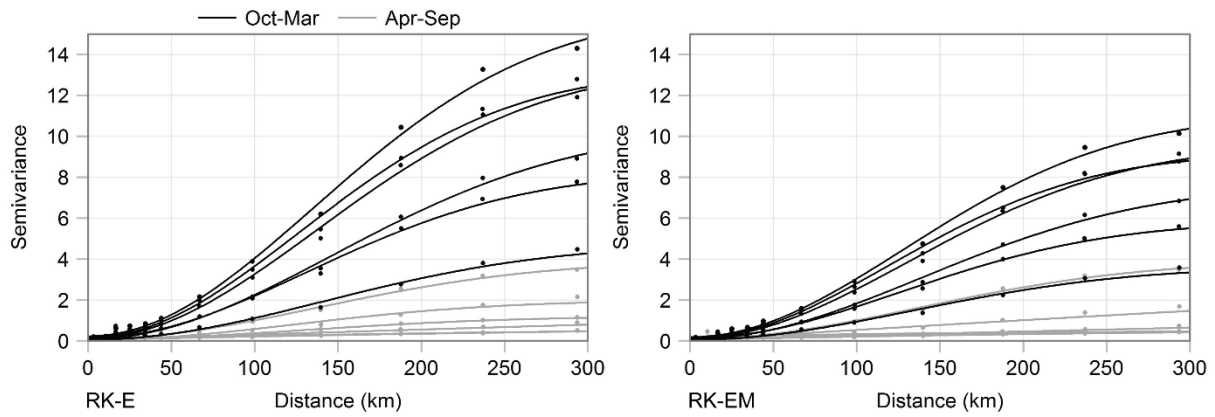


Figure 2.2: Monthly empirical and modelled variograms used for regression kriging of maximum temperature climate normal using elevation (E) and standardised day time MODIS LST (M) as independent covariates.

The exponential model was used exclusively to fit models to empirical variograms of minimum temperature regression residuals (Figure 2.3). The topographic index of relative elevation was effective in reducing residual variance, especially during cooler months (April to September) when compared against the elevation only model. Models using the standardised night time MODIS LST showed the lowest residual variance and shortest effective variogram ranges across all months. Despite these short effective ranges, the interpolated predictions consistently performed better than the regression component alone.

The monthly variability in RMSE for maximum and minimum temperature climate normals using a subset of the best performing models is illustrated in Figure 2.4. The addition of standardised day time MODIS values improves maximum temperature performance during the warmer months between October and April (1.4 – 11.2% reduction in RMSE). The relative performance of each minimum temperature climate normal model was consistent throughout the year, with the partial trivariate spline using standardised night time MODIS values and the topographic index providing the largest improvement in comparison to the partial bivariate spline (32.8 – 42.2% reduction in RMSE).

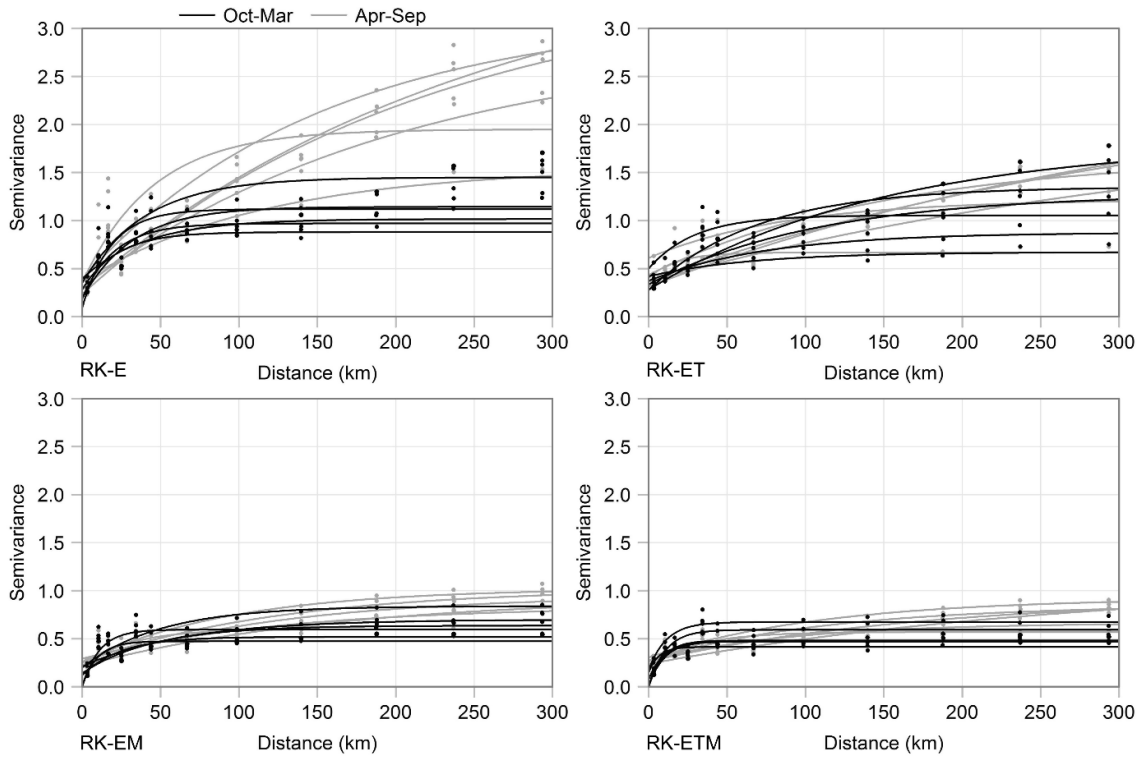


Figure 2.3: Monthly empirical and modelled variograms used for regression kriging of minimum temperature climate normal (1981–2010) using elevation (E), a topographic index (T) and standardised night time MODIS LST (M) as independent covariates.

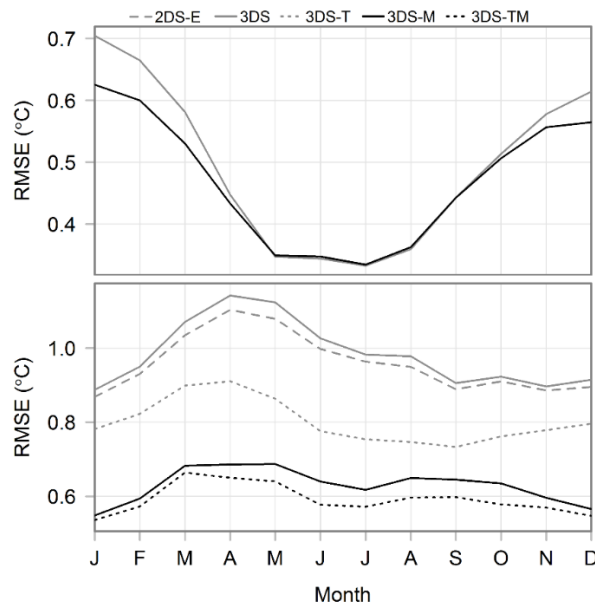


Figure 2.4: Cross-validated RMSE of monthly climate normal (1981-2010) for maximum (top) and minimum (bottom) temperature using full trivariate splines (3DS), partial trivariate splines (3DS-T, 3DS-M, 3DS-TM) and partial bivariate splines (2DS-E). Elevation (E), topographic index (T) and standardised MODIS values (M) are used as independent covariates where indicated in the model suffix.

Cross-validated error statistics for daily maximum temperature and daily minimum temperature are presented in Table 2.2. As with the climate normal analysis, daily anomalies performed best when using the MODIS corrected variants of the partial trivariate spline. A further improvement in minimum temperature performance was also achieved with the addition of the topographic index of relative elevation.

Table 2.2: Spatially and temporally pooled cross-validated error statistics for daily maximum and minimum temperature anomalies (January 1981 – August 2014). Climate normals used to calculate anomalies are interpolated using bivariate splines (2DS) and trivariate splines (3DS) using combinations of elevation (E), topographic index (T) and standardised MODIS values (M) as independent covariates.

	r^2	MAE	RMSE	RSR	BIAS
Maximum Temperature (°C)					
3DS	0.97	0.82	1.20	0.17	0.01
3DS-M	0.97	0.81	1.19	0.17	0.00
Minimum Temperature (°C)					
2DS-E	0.87	1.34	1.81	0.36	0.04
2DS-ET	0.88	1.29	1.73	0.34	0.02
3DS	0.87	1.35	1.83	0.37	0.02
3DS-T	0.88	1.29	1.73	0.34	0.01
3DS-M	0.89	1.24	1.65	0.33	0.00
3DS-TM	0.89	1.22	1.63	0.33	0.00

r^2 = coefficient of determination, MAE = mean absolute error, RMSE = root mean square error, RSR = ratio of the RMSE to the standard deviation of the observations, BIAS = mean error.

Spatial and temporal analyses of RMSE for all models shown in Table 2.2 are summarised in Appendix 2.A and 2.B. Model performance tends to decrease in the eastern regions of Victoria, particularly in high elevation areas with low weather station density. Daily maximum temperature shows a seasonal trend in RMSE which is not reflected in the RSR, suggesting that this is due to increased temperatures rather than a decrease in interpolation accuracy during the summer months. Temporal variability in RMSE for minimum temperature does not appear to be seasonally dependent.

Mean annual temperature and mean annual diurnal range residuals, calculated by subtracting the VECD from the VTCD, VECD+M and VTCD+M, are illustrated in Appendix 2.C. All models using standardised MODIS values as covariates demonstrate the largest variability in residual values for both mean annual temperature and mean annual diurnal range. The VTCD mean annual temperature residuals range between -1.3 and 1.8°C, compared with

a range of -1.2 to 2.4°C for the VECD+M and -1.5 to 2.0°C for the VTCD+M. Mean annual diurnal range residuals range between -3.5 and 2.7°C for the VTCD, compared with a range of -4.4 to 2.9°C for the VECD+M and -3.6 to 3.3°C for the VTCD+M.

The cumulative distribution of mean annual temperature and mean annual diurnal range residuals across Victoria are illustrated in Figure 2.5. Mean annual temperatures are lower than the elevation only model (VECD) in 58% of cells for the VTCD, and 65% of cells for both the VECD+M and VTCD+M. Mean annual diurnal ranges are higher than the elevation only model (VECD) in 58% of cells for the VTCD, 62% of cells for both the VECD+M and VTCD+M.

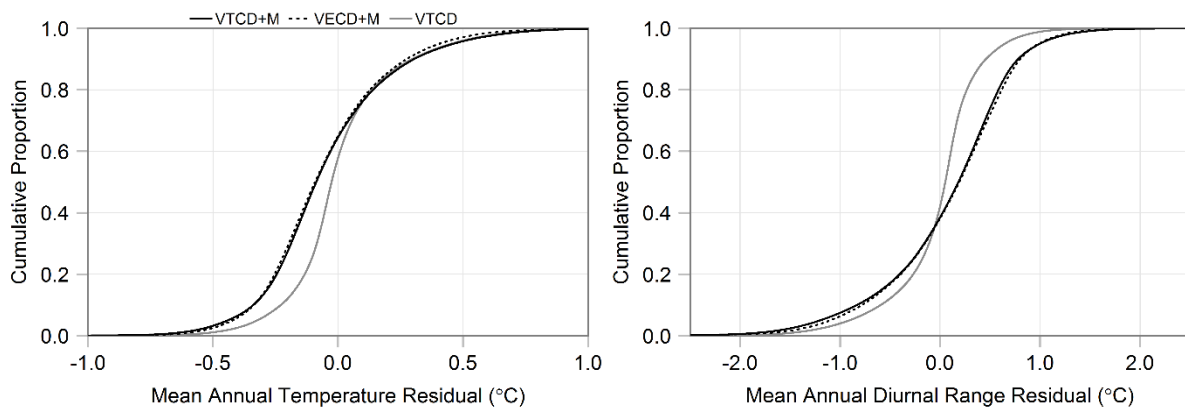


Figure 2.5: Cumulative distribution of mean annual temperature and mean annual diurnal range residuals throughout Victoria ($n = 376,834$), calculated by subtracting the Victorian elevation climate dataset (VECD) from the Victorian topo-climate dataset (VTCD), Victorian elevation plus MODIS dataset (VECD+M) and the Victorian topo-climate plus MODIS dataset (VTCD+M). Extreme values have been constrained for visual clarity.

The transect illustrated in Figure 2.6 demonstrates model behaviour in topographically complex terrain for mean annual temperature, mean annual diurnal range and mean annual minimum temperature when calculated using the VECD, VTCD, VECD+M, VTCD+M, WorldClim and AWAP climate normals. Using the topographic index and standardised MODIS LST values as covariates results in lower minimum temperatures predicted in valleys and higher values predicted on slopes. As a consequence of this behaviour, these models also predict broader diurnal ranges in valleys and narrower diurnal ranges on slopes. The trends observed for mean annual minimum temperature are reflected in mean annual temperature. WorldClim and AWAP climate normals demonstrate spatial homogenisation and reduced climatic variability when using coarser resolution data products.

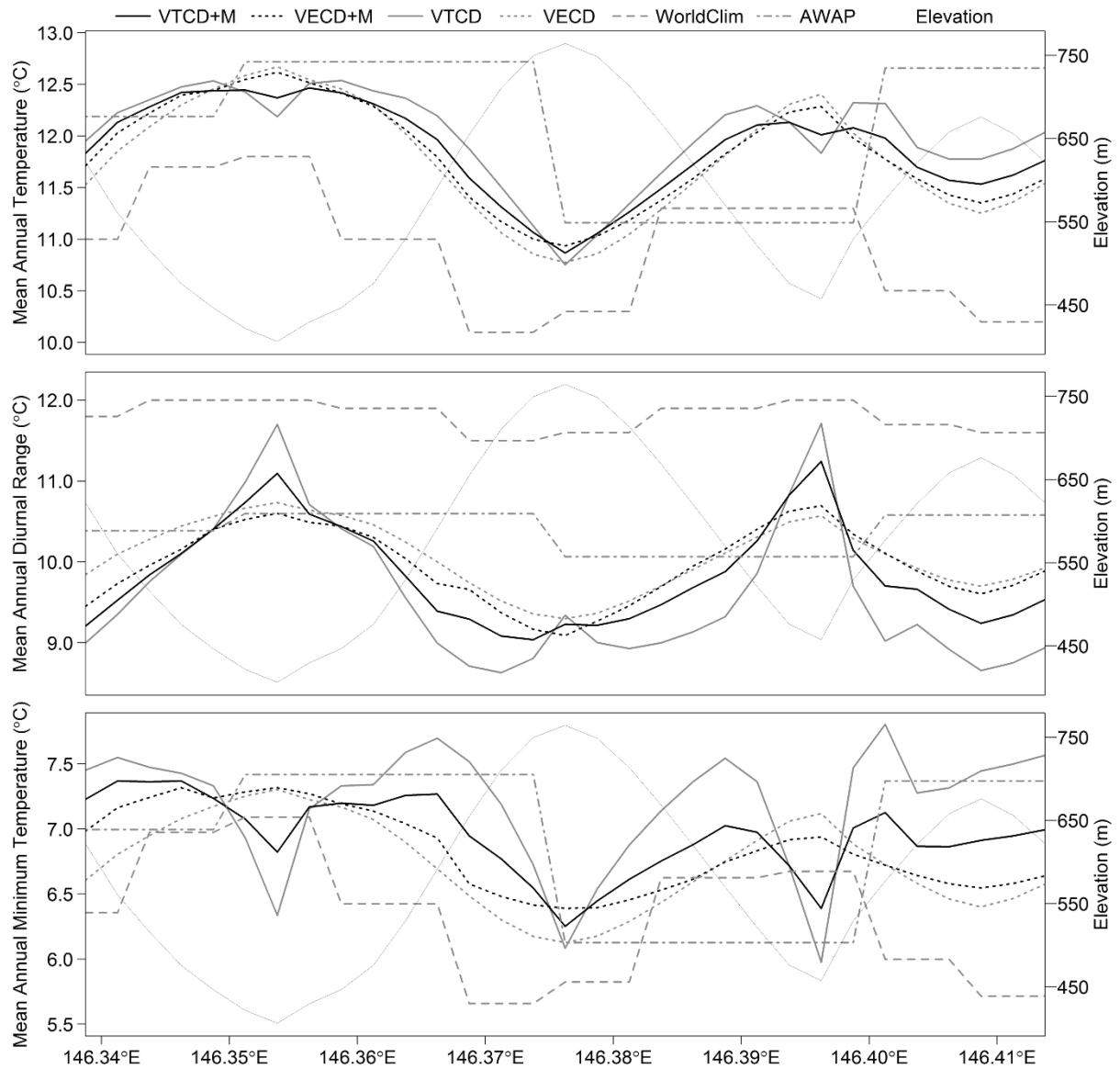


Figure 2.6: Mean annual temperature, mean annual diurnal range and mean annual minimum temperature across a transect (approximately 7.75 km) running west to east (146.339°-146.414 °E, 37.741°S) across two valleys. Values calculated using the Victorian elevation climate dataset (VECD; 1981–2010; $n = 31$), Victorian topo-climate dataset (VTCD; 1981–2010; $n = 31$), Victorian elevation plus MODIS dataset (VECD+M; 1981–2010; $n = 31$), Victorian topo-climate plus MODIS dataset (VTCD+M; 1981–2010; $n = 31$), WorldClim dataset (1950–2000; $n = 10$) and AWAP dataset (1961–1990; $n = 4$).

Boxplots (Figure 2.7) illustrate the range and variability of values shown in Figure 2.6 for each dataset. Both the WorldClim and AWAP datasets result in very narrow diurnal ranges across the transect. This is not reflected in the VECD dataset and further highlights the impacts of coarser spatial scales across topographically complex terrain.

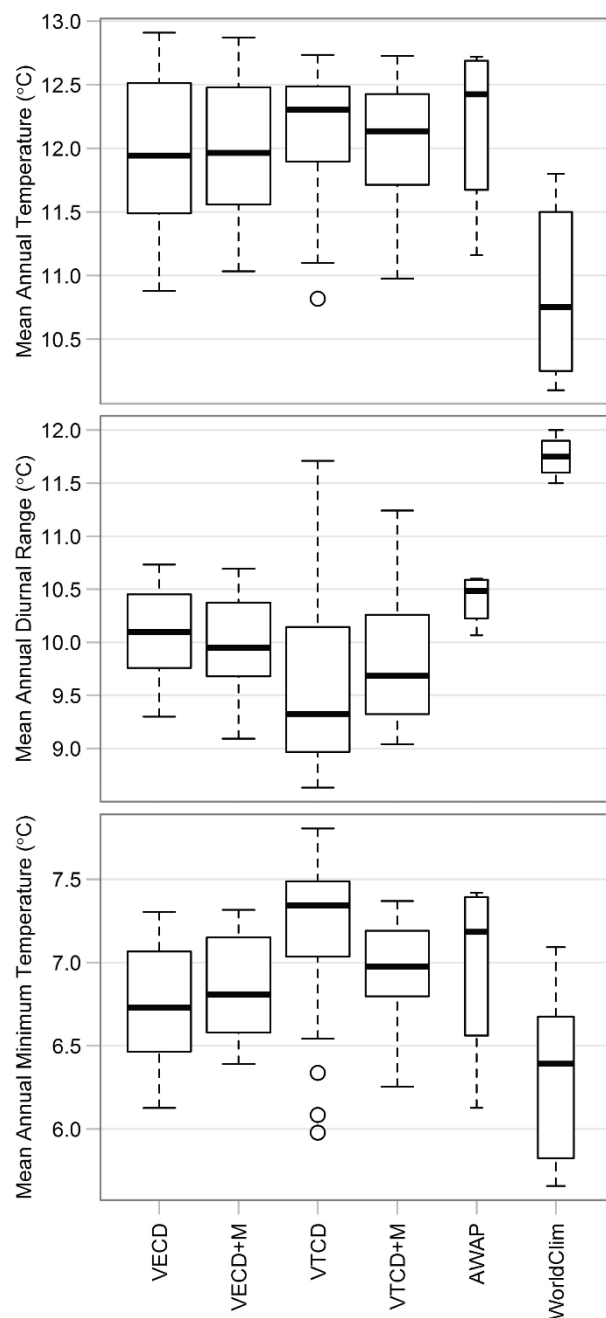


Figure 2.7: Boxplots of mean annual temperature, mean annual diurnal range and mean annual minimum temperature across a transect (approximately 7.75 km) running west to east (146.339°-146.414 °E, 37.741°S) across two valleys. Values calculated using the Victorian elevation climate dataset (VECD; 1981–2010; $n = 31$), Victorian topo-climate dataset (VTCD; 1981–2010; $n = 31$), Victorian elevation plus MODIS dataset (VECD+M; 1981–2010; $n = 31$), Victorian topo-climate plus MODIS dataset (VTCD+M; 1981–2010; $n = 31$), WorldClim dataset (1950–2000; $n = 10$) and AWAP dataset (1961–1990; $n = 4$).

2.4. DISCUSSION

The results of this study reaffirm that trivariate splines, which allow for a spatially varying dependence upon elevation, are robust for temperature interpolation (Hutchinson 1995; New et al. 2002; Hijmans et al. 2005; Hutchinson et al. 2009). Partial trivariate splines consistently performed well when using standardised MODIS LST values and the topographic index as independent covariates for minimum temperature. The magnitude of performance improvement suggests that these variables may be particularly useful for improving climatological surfaces; especially so considering that minimum temperatures form a component of many derived climate variables with ecological significance (i.e. vapour pressure deficit, potential evapotranspiration, aridity indices, bioclimatic variables). The benefits of using remote sensing data were much less pronounced for maximum temperature; however, an improvement was achieved during the warmer months. This is potentially due to the use of standardised meteorological weather stations and the scale at which maximum temperatures are altered by microclimatic conditions. The partial bivariate spline with a fixed dependence upon elevation; however, did perform slightly better than the full trivariate spline for minimum temperature. This is potentially due the spatial extent of the study which can lead to improved temperature interpolation when fixed lapse rates are used within a restricted area (Hutchinson et al. 2009; Hutchinson & Xu 2013). Partial bivariate splines consistently performed better than regression kriging, but only by a small margin. These methods can be expected to produce very similar results under optimal sampling conditions (Boer et al. 2001). Regression kriging consistently outperformed the regression component alone, which suggests that the variogram models used were sufficient to characterise spatial dependence of regression residuals across the state.

The daily error statistics presented should be interpreted with caution as they may be biased towards point locations where there are a larger number of records. Several weather stations with long term records were among the poorest performing locations during cross-validation. For example, the Wilsons Promontory Lighthouse station (146.42° E, 39.13° S) consistently cross-validated poorly across all methods, yet has a near complete observation record throughout the study period. When interpolating daily surfaces, it is highly likely that the prediction error at these locations would be much lower than the cross-validated estimates.

The magnitude of observed cross-validation error is, however, within reasonable ranges when assessed against previous Australian studies by Jeffrey et al. (2001) and Jones et al. (2009).

One of the key advantages of calibrating climate normal surfaces based on the existing weather station network is that anomaly interpolation can also be used to generate long term daily datasets without the need for post-processing or long-term field based observations. Furthermore, interpolation algorithms are able to identify and exclude suspect records and are not subject to spatial discontinuity that can arise when applying elevational lapse rates against the closest weather station observation. These daily surfaces are therefore suitable for use with process-based models that require data with a high spatial and temporal resolution. For example, the TACA-GEM model used by Mok et al. (2012) to model tree species response to climate change and variability in south east Australia requires daily data which limited the spatial resolution of analyses, requiring interpolation of model outcomes to finer scales. In addition, incorporating cold air drainage processes into daily datasets may be beneficial for process-based microclimate models such as Niche Mapper (Kearney et al. 2014) which are commonly run using coarse resolution daily temperature data that has been downscaled using elevational lapse rates.

The topographic index improved minimum temperature model performance over models that only used elevation as a predictor variable, which is consistent with previous studies by Daly et al. (2002; 2007) and Ashcroft and Gollan (2012) that have successfully used relative elevation metrics to characterise cold air drainage regimes at spatial scales ranging from 4 km to 25 m. Extracting spatial covariates at finer spatial resolutions (i.e. 25 m) is problematic without extensive field based observations, as the positional error of the existing Australian weather station network can in some cases be up to 1 km. Exploratory data analysis demonstrated consistent trends in model coefficients and the spatial variability of the topographic index was well represented by the weather station network, indicating that there were minimal detrimental effects to using the 250 m grid resolution for model calibration. The seasonal trends observed for relative elevation coefficients also suggest that a spatially varying dependence upon the topographic index may be advantageous at broader spatial extents and warrants further investigation. One of the core advantages of using a topographic index to improve temperature interpolation performance is that it is compatible with historical analysis in addition to climate change projections, unlike remotely sensed data that are characteristic of current conditions.

The use of standardised night time MODIS LST values demonstrated a large improvement in minimum temperature interpolation performance throughout Victoria. The incorporation of remote sensing data in this study was intentionally simple to ensure compatibility with the anomaly interpolation method and to minimise the effects of missing pixels, which is common in daily and 8-day composite MODIS LST surfaces for Victoria. Generating climate normals using standardised MODIS LST data comes with several advantages and limitations. This data indirectly captures microclimatic effects of land use such as those driven by vegetation cover and urbanisation; however, these effects may be misrepresented in regions where anthropogenic or natural disturbance has occurred prior to and between 2000 and 2010. Standardised MODIS LST values therefore cannot be directly used to improve climate interpolation performance for historical data or projection of climate change scenarios due to the limitations imposed by continuous land use changes. The data is also somewhat limited by the relatively coarse resolution (approx. 1 km) of the LST product which is likely to introduce smoothing effects on prediction surfaces. Despite these limitations, minimum temperature climate normals cross-validate well using MODIS data and may be useful for landscape scale research and applications such as modelling current species distributions, fire weather forecasting, agricultural modelling, and short term climate forecasts. MODIS calibrated prediction surfaces are also likely to be advantageous for studies conducted in regions where the landscape has remained relatively static over time.

The VTCD, VECD+M and VTCD+M datasets generated in this study demonstrate that the distribution of temperature is much more complex than can be captured by models that rely on elevation as the sole topographic predictor. This may be especially important for species with narrow bioclimatic envelopes or those predisposed to the understory, valleys, gullies or ridges, and also for the identification of climatic refugia. Transects and boxplots presented in Figure 2.6 and Figure 2.7 demonstrate the importance of spatial scale in predicting temperatures across topographically complex terrain, particularly so considering the differences in variability when comparing increasingly coarse representations of diurnal range. The accuracy of bioclimatic variables that represent long-term mean conditions is critical as they are highly utilised in correlative analyses and for characterising climatic conditions at field sites. Daily data also provides opportunities to quantify the severity and length of climate extremes and inter-annual variability. Incorporating extreme climate years or events can be critical for modelling the distributions of species (Zimmermann et al. 2009). Fine scale daily

data may provide opportunities to develop bioclimatic indices that are based on daily and/or monthly variability which cannot be captured by monthly long term conditions.

2.5. CONCLUSION

The existing historical weather station network in Victoria can be utilised to generate climate datasets of high spatial and temporal resolution that can characterise the effects of land use types and mesoscale processes such as cold air drainage which are influenced by local topographic complexity. Capturing fine scale topographic drivers of temperature will assist in bridging the gap between statistical interpolations and process-based microclimate models without the need for post-processing. These temperature datasets may improve species distribution modelling, calculation of aridity and drought indices, and assessments of fire risk by incorporating the high degree of spatial variability in climate variables that exists in topographically complex landscapes but cannot be accounted for with methods that rely on elevational lapse rates alone.

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2.7. APPENDICES

APPENDIX 2.A: SPATIAL AND TEMPORAL ANALYSIS OF DAILY MAXIMUM TEMPERATURE CROSS-VALIDATION STATISTICS

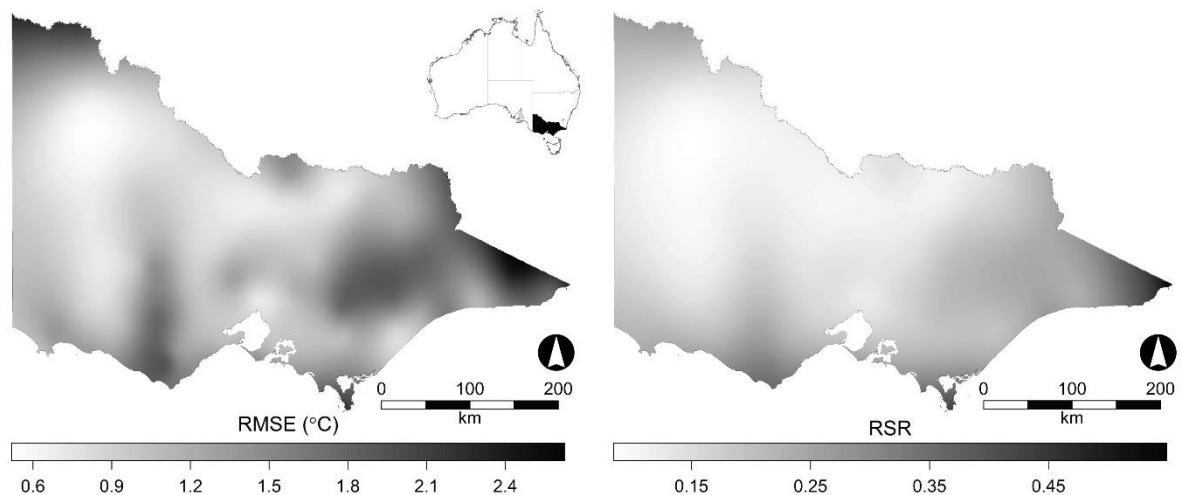


Figure 2.A.1: Cross-validated root mean squared error (RMSE) and ratio of the RMSE to the standard deviation of the observations for daily maximum temperature anomalies (January 1981 – August 2014). Climate normal surfaces used for calibration were interpolated with trivariate splines. Error statistics were interpolated using bivariate splines.

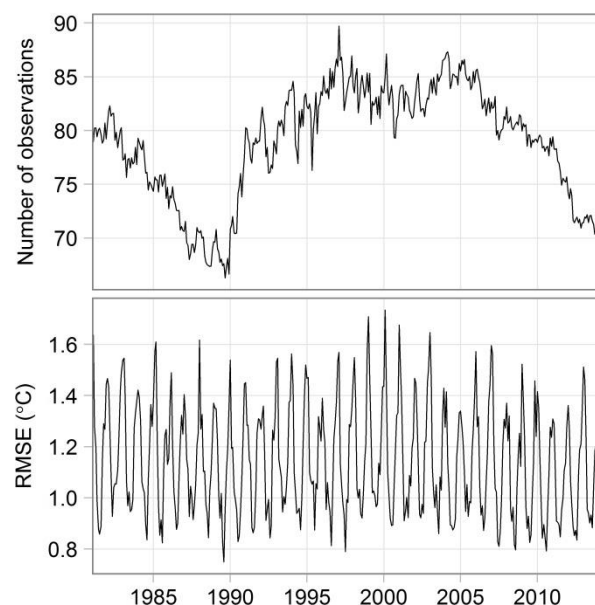


Figure 2.A.2: Mean monthly number of observations and root mean squared error (RMSE) for daily maximum temperature anomalies. Climate normal surfaces used for calibration were interpolated with trivariate splines.

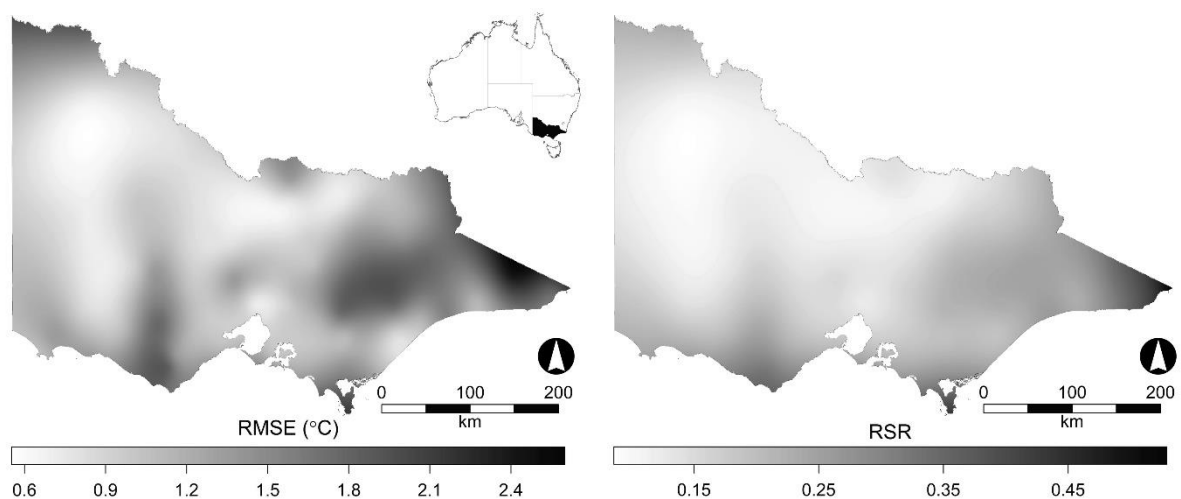


Figure 2.A.3: Cross-validated root mean squared error (RMSE) and ratio of the RMSE to the standard deviation of the observations for daily maximum temperature anomalies (January 1981 – August 2014). Climate normal surfaces used for calibration were interpolated with partial trivariate splines using standardised day time MODIS land surface temperature as an independent covariate. Error statistics were interpolated using bivariate splines.

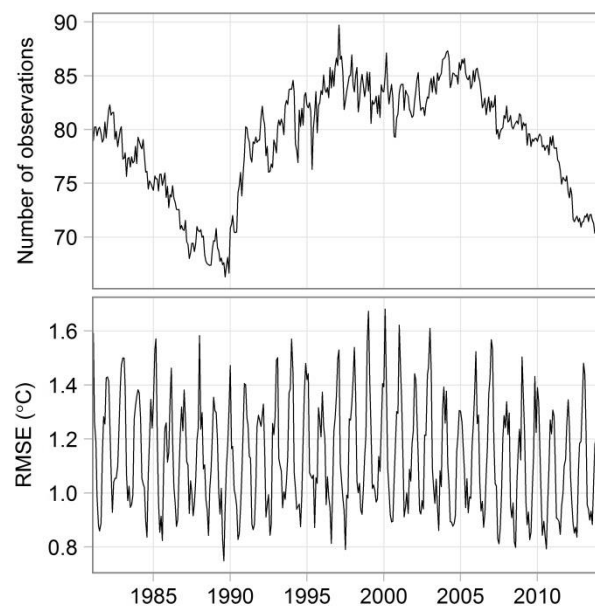


Figure 2.A.4: Mean monthly number of observations and root mean squared error (RMSE) for daily maximum temperature anomalies. Climate normal surfaces used for calibration were interpolated with partial trivariate splines using standardised day time MODIS land surface temperature as an independent covariate.

APPENDIX 2.B: SPATIAL AND TEMPORAL ANALYSIS OF DAILY MINIMUM TEMPERATURE CROSS-VALIDATION STATISTICS

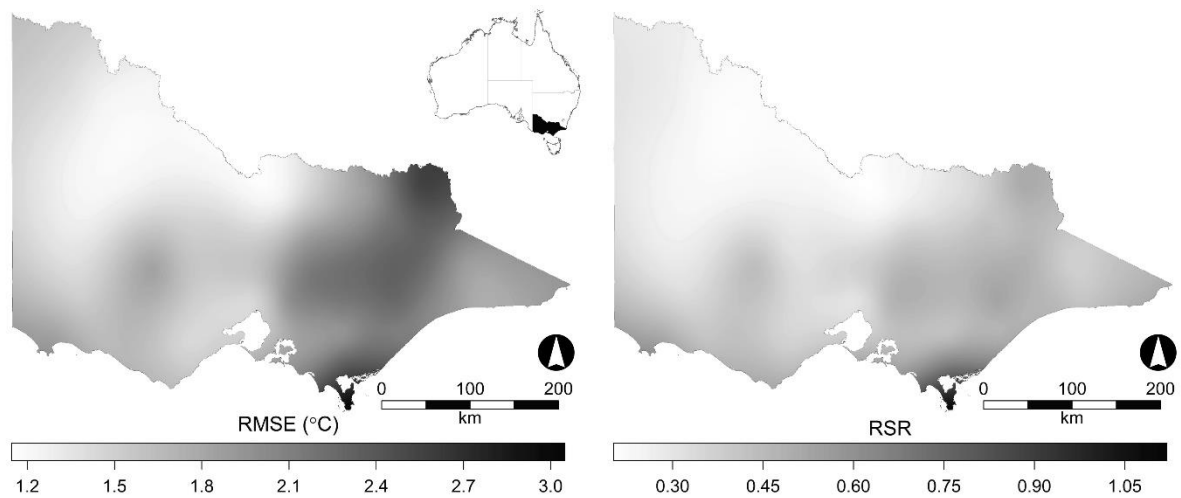


Figure 2.B.1: Cross-validated root mean squared error (RMSE) and ratio of the RMSE to the standard deviation of the observations for daily minimum temperature anomalies (January 1981 – August 2014). Climate normal surfaces used for calibration were interpolated with partial bivariate splines using elevation as an independent covariate. Error statistics were interpolated using bivariate splines.

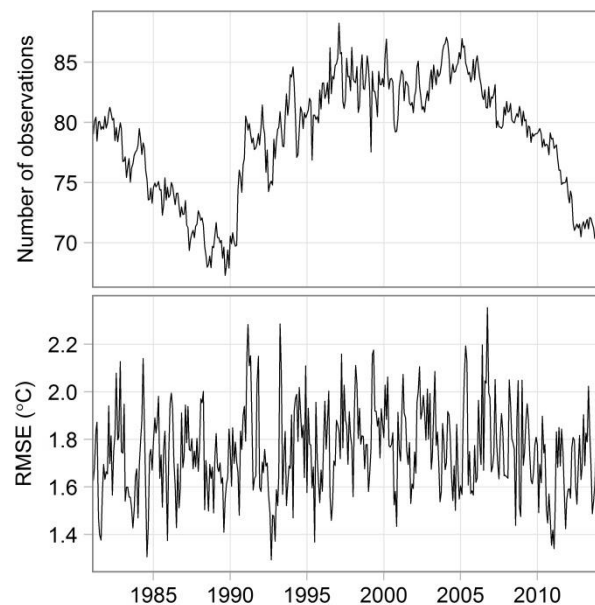


Figure 2.B.2: Mean monthly number of observations and root mean squared error (RMSE) for daily minimum temperature anomalies. Climate normal surfaces used for calibration were interpolated with partial bivariate splines using elevation as an independent covariate.

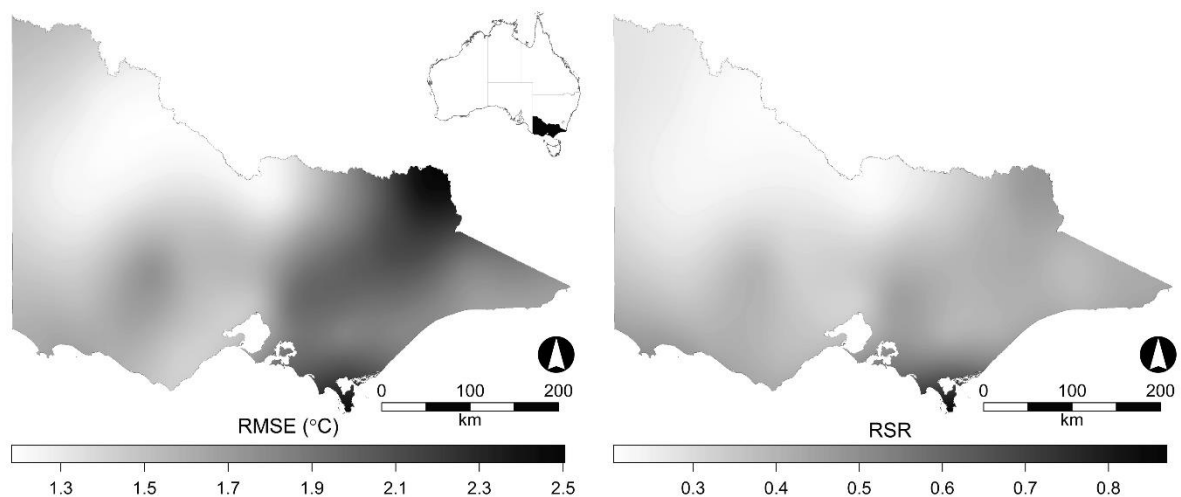


Figure 2.B.3: Cross-validated root mean squared error (RMSE) and ratio of the RMSE to the standard deviation of the observations for daily minimum temperature anomalies (January 1981 – August 2014). Climate normal surfaces used for calibration were interpolated with partial bivariate splines using elevation and a topographic index as independent covariates. Error statistics were interpolated using bivariate splines.

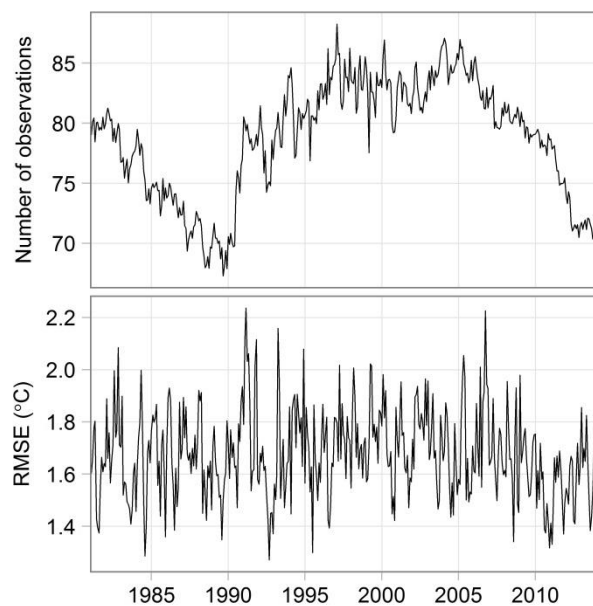


Figure 2.B.4: Mean monthly number of observations and root mean squared error (RMSE) for daily minimum temperature anomalies. Climate normal surfaces used for calibration were interpolated with partial bivariate splines using elevation and a topographic index as independent covariates.

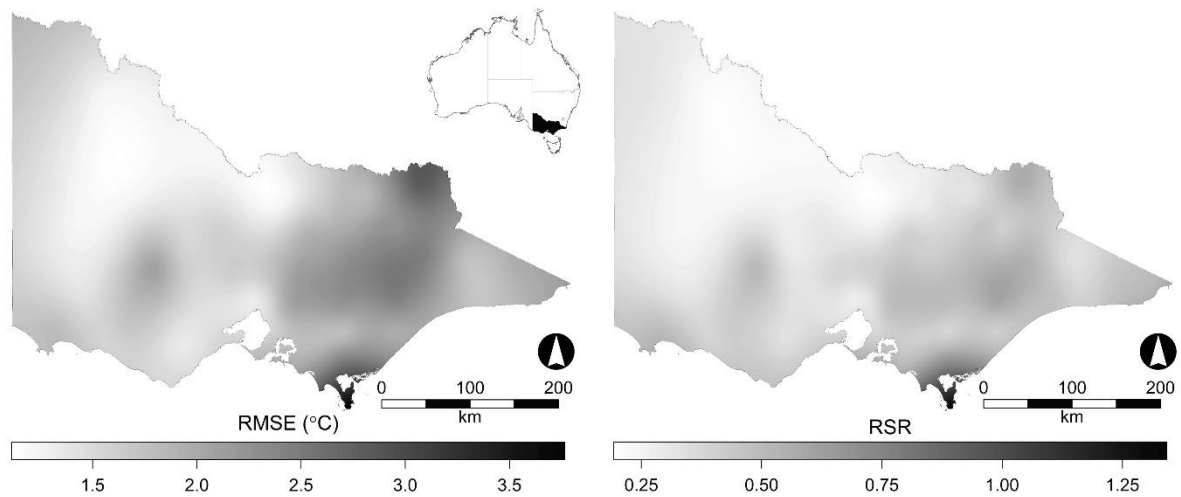


Figure 2.B.5: Cross-validated root mean squared error (RMSE) and ratio of the RMSE to the standard deviation of the observations for daily minimum temperature anomalies (January 1981 – August 2014). Climate normal surfaces used for calibration were interpolated with trivariate splines. Error statistics were interpolated using bivariate splines.

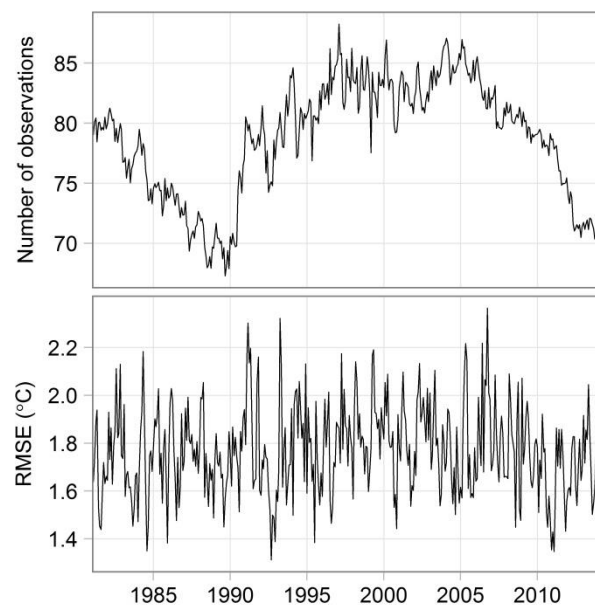


Figure 2.B.6: Mean monthly number of observations and root mean squared error (RMSE) for daily minimum temperature anomalies. Climate normal surfaces used for calibration were interpolated with trivariate splines.

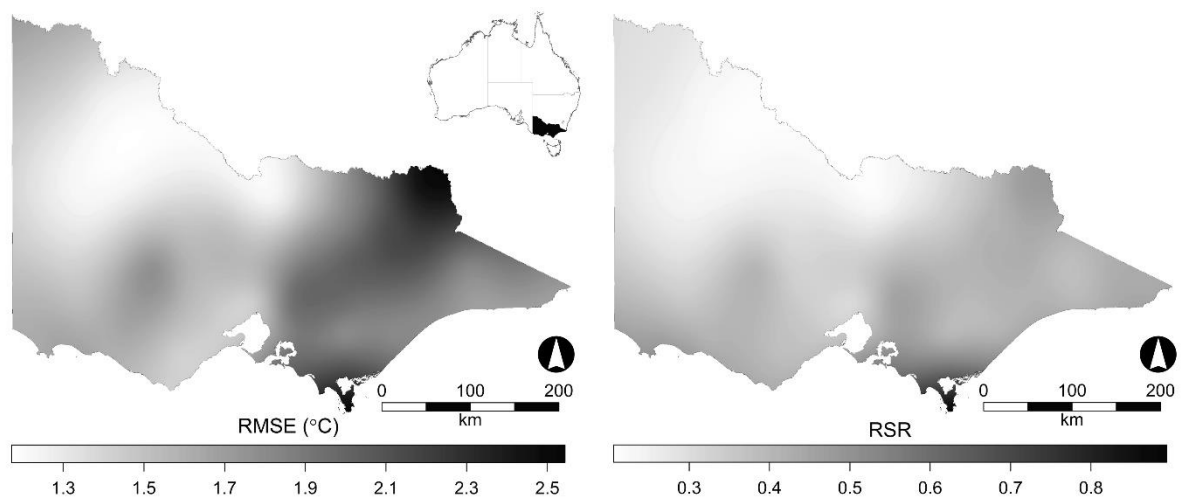


Figure 2.B.7: Cross-validated root mean squared error (RMSE) and ratio of the RMSE to the standard deviation of the observations for daily minimum temperature anomalies (January 1981 – August 2014). Climate normal surfaces used for calibration were interpolated with partial trivariate splines using a topographic index as an independent covariate. Error statistics were interpolated using bivariate splines.

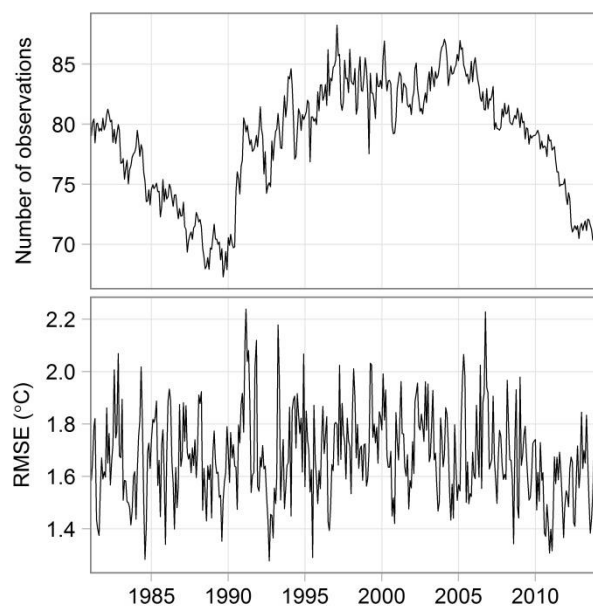


Figure 2.B.8: Mean monthly number of observations and root mean squared error (RMSE) for daily minimum temperature anomalies. Climate normal surfaces used for calibration were interpolated with partial trivariate splines using a topographic index as an independent covariate.

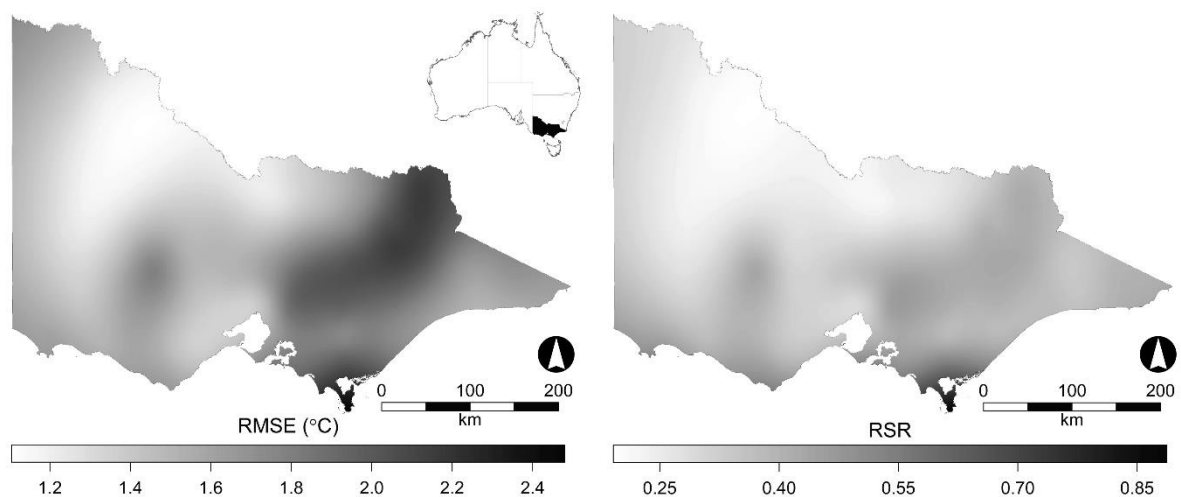


Figure 2.B.9: Cross-validated root mean squared error (RMSE) and ratio of the RMSE to the standard deviation of the observations for daily minimum temperature anomalies (January 1981 – August 2014). Climate normal surfaces used for calibration were interpolated with partial trivariate splines using standardised night time MODIS land surface temperature as an independent covariate. Error statistics were interpolated using bivariate splines.

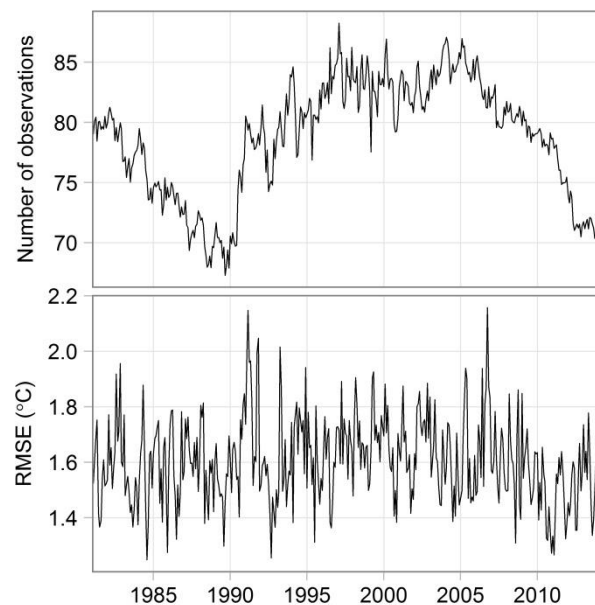


Figure 2.B.10: Mean monthly number of observations and root mean squared error (RMSE) for daily minimum temperature anomalies. Climate normal surfaces used for calibration were interpolated with partial trivariate splines using standardised night time MODIS land surface temperature as an independent covariate.

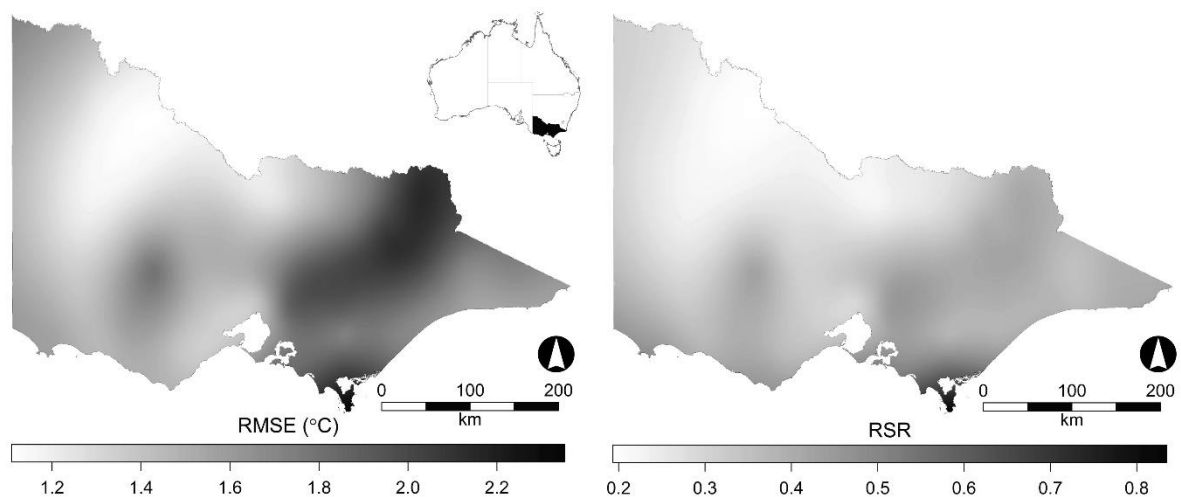


Figure 2.B.11: Cross-validated root mean squared error (RMSE) and ratio of the RMSE to the standard deviation of the observations for daily minimum temperature anomalies (January 1981 – August 2014). Climate normal surfaces used for calibration were interpolated with partial trivariate splines using a topographic index and standardised night time MODIS land surface temperature as independent covariates. Error statistics were interpolated using bivariate splines.

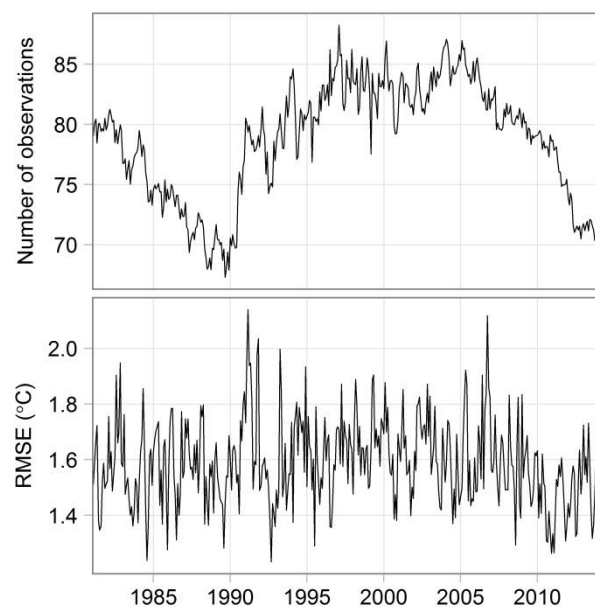


Figure 2.B.12: Mean monthly number of observations and root mean squared error (RMSE) for daily minimum temperature anomalies. Climate normal surfaces used for calibration were interpolated with partial trivariate splines using a topographic index and standardised night time MODIS land surface temperature as independent covariates.

APPENDIX 2.C: SPATIAL DISTRIBUTION OF MEAN ANNUAL TEMPERATURE AND MEAN ANNUAL DIURNAL RANGE RESIDUALS OBTAINED BY SUBTRACTING THE VICTORIAN ELEVATION CLIMATE DATASET (VECD) FROM THE VICTORIAN TOPO-CLIMATE DATASET (VTCD), VICTORIAN ELEVATION PLUS MODIS DATASET (VECD+M) AND THE VICTORIAN TOPO-CLIMATE PLUS MODIS DATASET (VTCD+M)

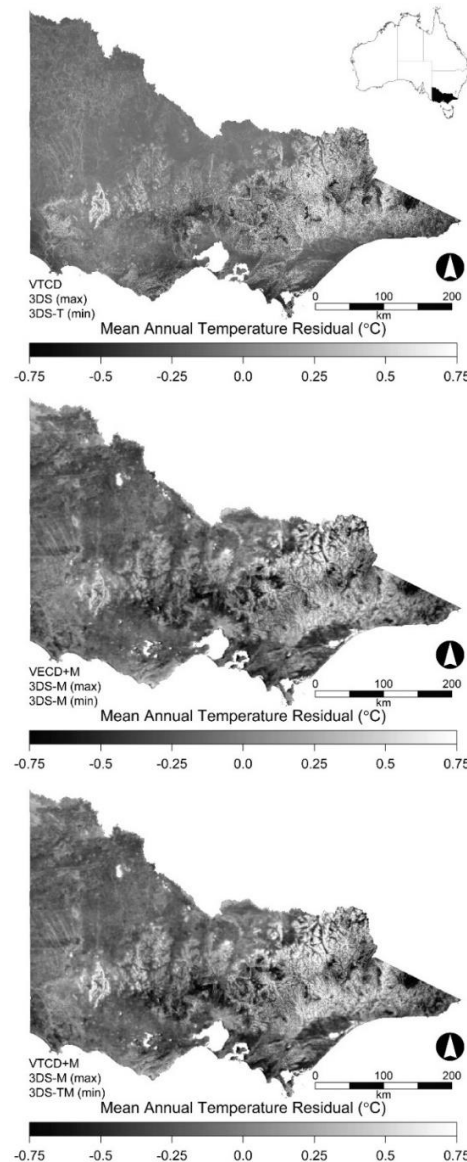


Figure 2.C.1: Mean annual temperature residuals calculated by subtracting the Victorian elevation climate dataset (VECD) from the Victorian topo-climate dataset (VTCD), Victorian elevation plus MODIS dataset (VECD+M) and the Victorian topo-climate plus MODIS dataset (VTCD+M). Maximum and minimum temperature values are interpolated using partial thin plate splines (PTPS) with combinations of elevation (E), topographic index (T) and standardised MODIS values (M) as independent covariates. Extreme values have been constrained for visual clarity.

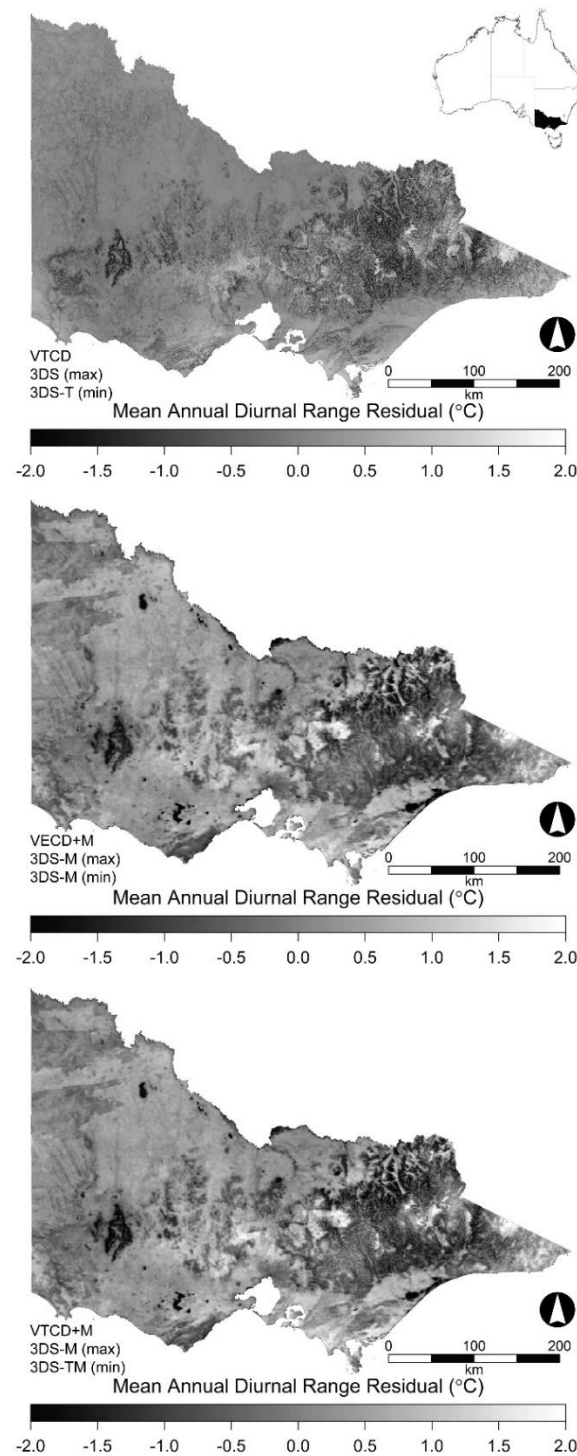


Figure 2.C.2: Mean annual diurnal range residuals calculated by subtracting the Victorian elevation climate dataset (VECD) from the Victorian topo-climate dataset (VTCD), Victorian elevation plus MODIS dataset (VECD+M) and the Victorian topo-climate plus MODIS dataset (VTCD+M). Maximum and minimum temperature values are interpolated using partial thin plate splines (PTPS) with combinations of elevation (E), topographic index (T) and standardised MODIS values (M) as independent covariates. Extreme values have been constrained for visual clarity.

APPENDIX 2.D: SPATIAL SUBSETS OF MEAN ANNUAL TEMPERATURE AND MEAN ANNUAL DIURNAL RANGE

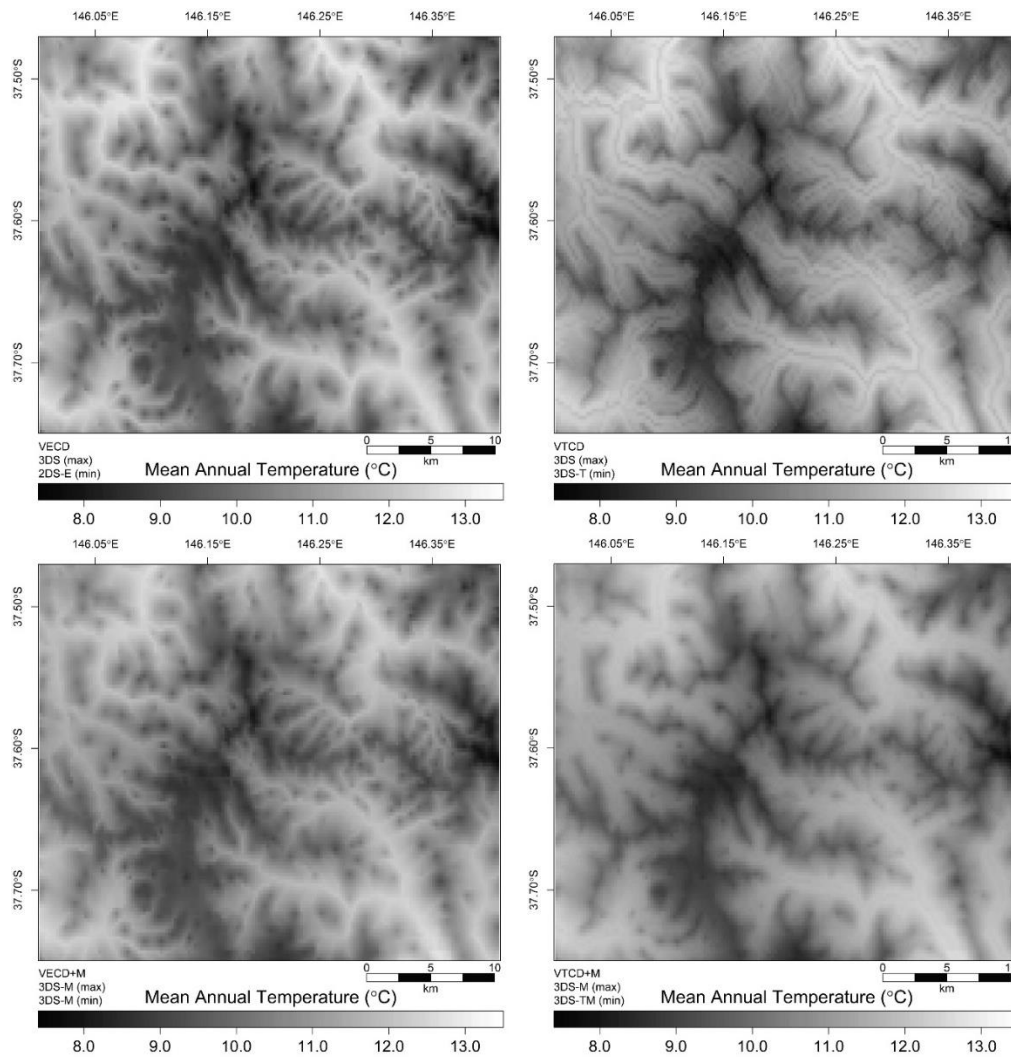


Figure 2.D.1: Spatial subsets of mean annual temperature (1981 – 2010) calculated using the Victorian elevation climate dataset (VECD), Victorian topo-climate dataset (VTCD), Victorian elevation plus MODIS dataset (VECD+M) and the Victorian topo-climate plus MODIS dataset (VTCD+M). Maximum and minimum temperature values are interpolated using bivariate or trivariate splines with combinations of elevation (E), topographic index (T) and standardised MODIS values (M) as independent covariates.

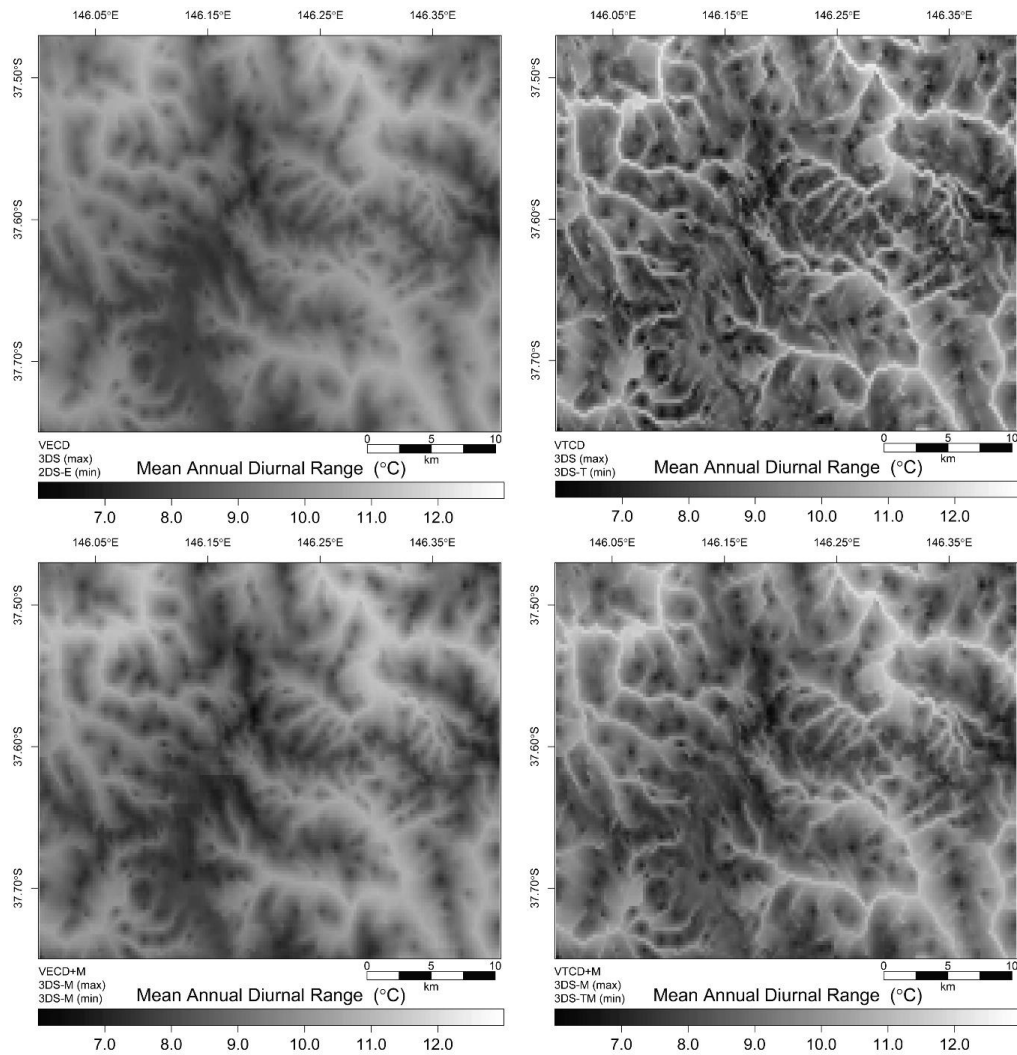


Figure 2.D.2: Spatial subsets of mean annual diurnal range (1981 – 2010) calculated using the Victorian elevation climate dataset (VECD), Victorian topo-climate dataset (VTCD), Victorian elevation plus MODIS dataset (VECD+M) and the Victorian topo-climate plus MODIS dataset (VTCD+M). Maximum and minimum temperature values are interpolated using bivariate or trivariate splines with combinations of elevation (E), topographic index (T) and standardised MODIS values (M) as independent covariates

3

CHAPTER THREE: ASSESSING THE TRANSFERABILITY OF EMERGING INTERPOLATION TECHNIQUES²

This chapter evaluates the transferability of the temperature interpolation methods developed and as part of the previous chapter to novel climates. In addition to temperature, vapour pressure and precipitation interpolation methods are also evaluated. The national weather station observations used in this chapter have not previously been included in global climate datasets, which provided an opportunity to also investigate the potential influence of observation density and associated biases that may arise in under sampled, topographically extreme landscapes. Monthly mean precipitation, vapour pressure, and temperature datasets were generated to make full use of the local weather station observations and to create a new national data resource for Bhutan.

3.1. INTRODUCTION

The Himalayas comprise some of the most complex and extreme topography in the world, forming a natural barrier between the Tibetan plateau and the low-lying plains of the Indian subcontinent. The mountain range spans a distance of approximately 2,400 km from west to east, reaching peaks of over 8,500 m above sea level (asl) and crossing through Bhutan, India, Nepal, China and Pakistan. Uplift of the Himalayas and the Tibetan plateau over the past 50 million years has had large impacts upon the evolution of the Asian monsoon and intensified aridity in central Asia (Zhinsheng et al. 2001). Historically, the region has been of great interest to climatologists (Hill 1881; Flohn 1970; Barry 2008); however, few studies have focused specifically on the climatology of Bhutan.

²This chapter has been published (Appendix A.2) as:

Stewart, S.B., Choden, K., Fedrigo, M., Roxburgh, S.H., Keenan, R.J., Nitschke, C.R., 2017. The role of topography and the north Indian monsoon on mean monthly climate interpolation within the Himalayan Kingdom of Bhutan. *International Journal of Climatology* 37(S1): 897-909. doi: 10.1002/joc.5045.

Bhutan has an extremely diverse climate given its small size, which is due to the highly variable and complex topographic features that comprise the landscape. The climate is expected to change considerably over the coming decades (Singh et al. 2011) with mean annual temperature projected to increase by up to 3.5 °C and mean annual regional precipitation projected to increase between 80 mm and 180 mm by the 2050s (Tse-ring et al. 2010). High resolution climate datasets can facilitate ecological and agricultural research and land management decisions, as the spatial distribution and productivity of vegetation is heavily dependent upon climatic conditions (Austin & Van Niel 2011; Elith & Franklin 2013). Currently there is a paucity of spatial climate datasets calibrated using ground-based station observations for Bhutan which limits the ability to conduct robust assessments of climate and climate change on forests and agricultural ecosystems.

The latitudinal position in addition to the topographic extremes and complexity of the Himalayan region means that the climate has some unusual features. Temperature lapse rates show distinct trends that are associated with the seasonal reversal of the north Indian monsoon (Kattel et al. 2013; 2015; Dorji et al. 2016) and tend to be suppressed during the humid, cloudy, and wet summer months. Increased levels of atmospheric moisture and the forced ascent of air against the Himalayas result in cloud formation, precipitation and an associated release of latent heat (Ohata et al. 1981; Whiteman 2000; Barry 2008; Krishnamurti et al. 2013), particularly at higher elevations (Kattel et al. 2013). The cloudy conditions also cause more solar radiation to be reflected during the day, leading to cooler temperatures at lower elevations (Kattel et al. 2013). Kattel (et al. 2013) found residual errors were much larger for minimum temperatures than for maximum temperatures in Nepal and attribute this result to nocturnal temperature inversions. Temperature inversions typically develop under clear, calm conditions. At night time, thermal stratification of air in the lower troposphere (as a result of radiative cooling, subsidence, or convection of warm air over regions of cooler air) can cause a decoupling of the slope and valley atmospheres in mountainous terrain (Geiger 1965; Whiteman 2000; Barry 2008; Daly et al. 2009). As a consequence, cold air pools develop in basins and valley bottoms, and slopes become warmer due to convective processes. While this phenomenon is typically more pronounced in regions of complex topography, it may also manifest in comparatively flat terrain (Barry 2008; Kattel et al. 2013). Much weaker inversions are observed under windy conditions, or where cloud cover and water vapour decrease net longwave radiation losses (Iijima & Shinoda 2000; Whiteman et al. 2007; Zardi & Whiteman 2013). The spatial distribution of minimum temperature is therefore heavily dependent upon local terrain, and

several studies have demonstrated that focal topographic metrics (Daly et al. 2007; Ashcroft & Gollan 2012) and thermal remote sensing data (Stewart & Nitschke 2017/Chapter 2) can be effective for improving minimum temperature interpolation performance.

Globally consistent climatologies such as WorldClim (Hijmans et al. 2005) and those developed by the Climatic Research Unit (CRU), University of East Anglia (New et al. 1999; New et al. 2002; Harris et al. 2014) can be used to extract climate data for most regions; however, they are somewhat limited for fine-scale ecological studies due to low spatial resolution and the variable density of suitable weather station data. The CRU suite of products are available at a spatial resolution of 18 km or 50 km, and are therefore limited in their ability to resolve the effects of fine scale topographic complexity on climate. Downscaling approaches (e.g. Wang et al. 2012) can be used to increase the spatial resolution of climate data; however, they typically rely on elevation dependencies and do not currently allow the incorporation of additional explanatory variables that can improve the quality of fine scale interpolations (Stewart & Nitschke 2017/Chapter 2). WorldClim was developed at a much higher spatial resolution of approximately 1 km but does not provide data on variables such as humidity, sunshine duration and wind speed that are important ecologically. One of the key challenges in developing these globally representative surfaces is the availability of suitable station observations that are of sufficient density to capture regional scale climatological processes. Many regions of the world are underrepresented within these databases (CRU 2016; NOAA 2016; Hijmans et al. 2010), which can result in poor interpolation performance (Hijmans et al. 2005). The networks of weather stations typically used for these analyses do not include locations within Bhutan (CRU 2016; NOAA 2016; Hijmans et al. 2010). For example, the stations used for the WorldClim dataset (Figure 3.1; Hijmans et al. 2010) are sparse given the topographic complexity in this region, and many of the weather stations are no longer operational, particularly in India near the southern border of Bhutan.

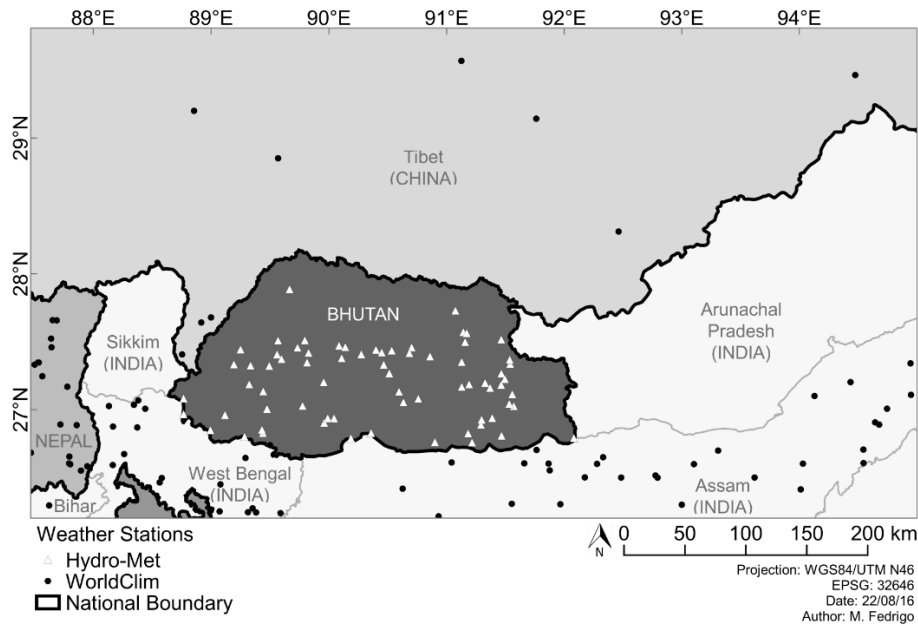


Figure 3.1: Weather stations used to generate climate surfaces for the present study (1986 – 2015; Department of Hydro-Met Services) and the WorldClim dataset (1950–2000; Hijmans et al. 2010).

Until recently, the network of weather stations operating within Bhutan had not been used to develop spatially representative climate datasets for the region. Dorji (et al. 2016) used linear and polynomial regressions to describe the distribution of seasonal temperature and precipitation across Bhutan. The equations developed by Dorji (et al. 2016) are broadly representative of the region; however, they retain residual error when generating prediction surfaces and do not account for a spatially varying dependence upon elevation. Furthermore, extrapolating precipitation into the northern regions of Bhutan using polynomial regression and excluding the effects of orography are likely to lead to oversimplified predictions of rainfall.

The WorldClim and CRU CL 2.0 (New et al. 2002) datasets have been generated using trivariate thin plate smoothing splines (Wahba 1990) which are robust for climate interpolation (Hutchinson 1995; Hutchinson et al. 2009). Thin plate splines allow for a spatially varying dependence on elevation and minimise residual error at calibration locations; both of which are significant advantages over alternative methods such as linear regression. The thin plate spline algorithm is comprised of an affine component which is used to fit the global trend (as a function of spline variables) and a local non-affine component that adjusts the local non-linear surface. Trivariate splines are most commonly fit with full spline dependence upon latitude, longitude and elevation. Additional independent covariates can be incorporated by extension to a partial spline model, which includes a parametric regression component (Bates et al 1987).

The objective of this study was to develop improved temperature, precipitation and vapour pressure datasets for Bhutan that address limitations of existing climate surfaces available for the region. This was done by using the local weather station network in conjunction with spline-based interpolation methods. The relative performance improvements that can be achieved by including thermal remote sensing data and local topographic metrics as partial spline dependencies when interpolating temperature variables were also assessed. These variables have recently demonstrated an improvement in temperature interpolation performance in topographically complex landscapes in southeast Australia (Stewart & Nitschke 2017/Chapter 2). The climate surfaces developed in this study were compared against the globally representative WorldClim (Hijmans et al. 2005) and CRU CL 2.0 (New et al. 2002) datasets in order to highlight the importance of spatial resolution and observation density when developing interpolated climate surfaces.

3.2. METHOD

3.2.1. STUDY EXTENT

Bhutan is a land-locked country located on the southern slopes of the eastern Himalayas, sharing borders with China to the north and India to the east, west and south. The largely mountainous country is 38,394 km² in area and ranges from approximately 100 m asl in the south to 7,500 m asl in the far north (Figure 3.2). The extreme range in elevation leads to highly variable climatic conditions within a distance spanning only 170 km in latitude (Norbu et al. 2003). Like many regions of Asia the climate of Bhutan is monsoonal. South-westerly winds bring moist air from the Bay of Bengal to Bhutan during the summer phase of the north Indian monsoon (Krishnamurti et al. 2013; Tamang 2014). The country has three distinct climatic zones; alpine, temperate and subtropical (NSB 2015). The climate is humid and subtropical in the southern plains and foothills (100 – 2,000 m asl), with heavy rainfall occurring during the summer monsoon. The inner Himalayan valleys of the central regions have a temperate climate (2,000 – 4,000 m asl); however, they often receive less rainfall than the surrounding slopes and ridges as cloud cover and precipitation are suppressed by strong up-valley and up-slope winds (Barry 2008; Whiteman 2000). The high Himalayas to the north experience a cold alpine climate (4,000 m asl and above) and a permanent snow line can be found above 4,800 m asl (Tamang 2014). In winter, the snow line across the eastern Himalayas can descend to around 3,000 m asl (Mani 1981).

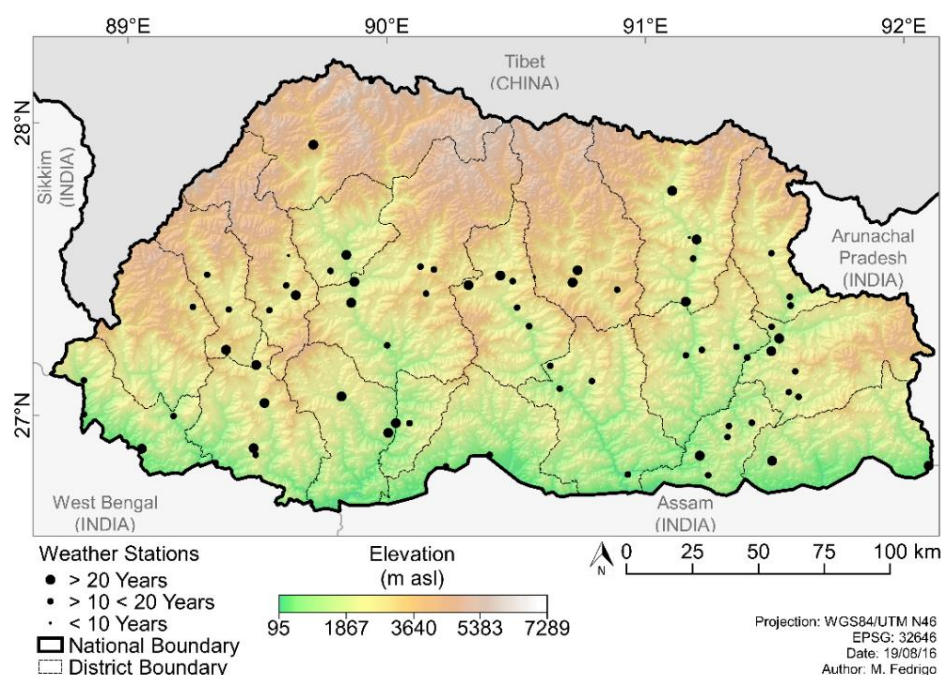


Figure 3.2: Digital elevation model of Bhutan (Jarvis et al. 2008) and the weather station network operating between 1986 and 2015.

The estimated population of Bhutan is 784,000 (as of 2016), and approximately 56% of people are employed in the agricultural sector (NSB 2015; UN Data 2016). Over 70% of the country is under forest cover (Figure 3.3; LCMP 2011; NASA LP DAAC 2016). Bhutan hosts a diverse range of vegetation and forest types (Ohsawa 1987; LCMP 2011; NBSAP 2014), owing to the complex topography and corresponding climatic variability. The subtropical climate zone is comprised of broadleaf, chir pine (*Pinus roxburghii*) and tropical lowland forest. Fir, mixed conifer, blue pine (*Pinus wallichiana*) and mixed broadleaf and conifer forest can be found in the temperate climate zone, and the alpine climate zone consists of meadows and scrubs.

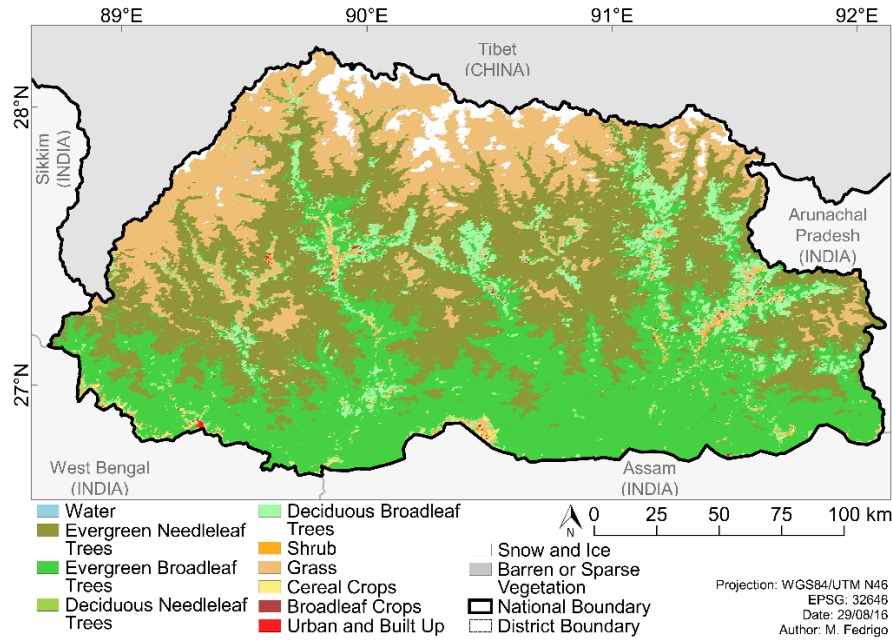


Figure 3.3: Dominant MCD12Q1 land cover classification (Friedl et al. 2010; NASA LP DAAC 2016) across Bhutan between 2000 and 2013 under the Plant Functional Type (PFT) scheme (Bonan et al. 2002).

3.2.2. DATASETS

Daily maximum temperature, minimum temperature, precipitation and relative humidity records for 71 weather stations operating between January 1986 and December 2015 were obtained from the Department of Hydro-Met Services (DHMS), Ministry of Economic Affairs, Bhutan. Latitude, longitude and elevation at each station were extracted from site metadata also provided by the DHMS. The network of stations used throughout the analysis was distributed across elevations ranging from 180 m asl to 3,537 m asl (Figure 3.1). The record length at each station was on average 19.6 years long, with a minimum of 6.7 years and maximum of 30 years of observations. Daily records were excluded where the maximum temperature was reported as lower than the minimum temperature (795 daily records), relative humidity was below 0% or above 100% (128 daily records), or the amount of precipitation was negative (7 daily records).

Estimates of daily vapour pressure, rather than observations of relative humidity, were used to ensure dependence upon elevation. Daily vapour pressure was derived from the saturation vapour pressure of the mean daily temperature and relative humidity (Abtew &

Melesse 2013). The mean daily temperature was calculated as the average of the maximum and minimum temperature. The saturation vapour pressure, e_s , was calculated using a reparameterisation (Alduchov & Eskridge 1996) of the August-Roche-Magnus equation (Lawrence 2005);

$$e_s(T) = 6.1094 \times \exp^{\frac{17.625 \times T}{243.04 + T}}$$

The daily vapour pressure, e , was then derived from the saturation vapour pressure at the mean temperature and relative humidity (RH);

$$e = e_s(T_{mean}) \times RH$$

Provisional climate normals (hereafter referred to as climate normals), representing the monthly mean conditions between 1986 and 2015, were calculated for maximum temperature, minimum temperature, precipitation and vapour pressure at each station. Monthly values were computed using daily observations prior to the calculation of monthly mean values. Monthly precipitation was calculated as the sum of daily precipitation where observations were available for each day of the month. Monthly mean temperature and vapour pressure were calculated as the mean of each daily observation where the following criteria were met; (1) no more than 10 missing days of data were allowed, and (2) no more than 4 consecutive days of missing data were allowed (WMO 2011). Calculating climate normals for any reference period may be biased due to short or incomplete records at different observation locations. A regression patching approach was tested to correct for any potential bias induced by short term records by regressing observations against neighbouring stations (Hopkinson et al. 2012; Stewart & Nitschke 2017/Chapter 2); however, this method did not produce reliable results. Monthly climate normals were therefore calculated for each station where at least 10 years of observations were available for each month (Hijmans et al. 2005) to ensure interpolation was supported by a sufficient number of data points in different locations and at the highest elevations.

Potential biases in short term means were investigated using interpolation variance and by analysing ranked residuals throughout the cross-validation procedure for each variable. Stations were identified as suspect where the calculated mean value was more than 3.6 standard deviations from the cross-validated prediction. This approach identified one suspect station which was subsequently removed from all analysis due to close proximity with neighbouring

stations and short record length (10 years for each month). The removal of additional short term records selected based on ranked residuals consistently led to decreased performance at neighbouring stations (including those with more than 20 years of data) and therefore they were retained throughout the analysis. Excluding the suspect station and those with less than 10 years of data resulted in a satisfactory spatial and temporal coverage, with the number of stations available for analysis reduced by between 6 and 11% for any variable or month.

The digital elevation model (DEM) used throughout the analysis was obtained from the CGIAR Consortium for Spatial Information (<http://srtm.csi.cgiar.org>). This was resampled to 7.5 arc seconds (approx. 225 m cell resolution at the equator) using the sink-filled 3 arc second (approx. 90 m cell resolution) Shuttle Radar Topography Mission (SRTM) dataset (Jarvis et al. 2008). One of the issues with interpolating precipitation across a fine resolution DEM is that the predictions are heavily influenced by local topography, leading to unrealistically large differences at very small spatial scales. As precipitation is not strongly correlated with elevation at distances up to 5 km to 10 km (Hutchinson 1998; Sharples et al. 2005), the original DEM was smoothed using a Gaussian filter for calibrating and predicting precipitation (Barnes 1964; Daly et al. 2007). The use of a focal filter to smooth elevation allows for precipitation surfaces to be generated at high resolution without extreme short range variability. The degree of smoothing is determined by the filter extent and standard deviation of the Gaussian distribution. The smoothing filter was applied with a circular search diameter of 35 cells (approx. 7.8 km) and a standard deviation of 10 cells using the System for Automated Geoscientific Analysis (SAGA) software package (Conrad et al. 2015). The required level of smoothing was determined by iteratively adjusting the standard deviation of the filter (5 to 25) and cross-validating precipitation climate normals (Appendix 3.A). Performance was optimal at a standard deviation of 10 cells, although the differences between each level of smoothing varied by less than 1.5% in RMSE. Geographic coordinates were expressed in decimal degrees and elevation expressed in kilometres during all analyses (Hutchinson 1995; Hutchinson 1998; Hutchinson 2009) to minimise error during cross-validation and surface generation.

The effects of topographic position on minimum temperature were assessed using a topographic index of relative elevation, which has been shown to improve model performance by representing the effect of overnight temperature inversions and cold air pooling processes (Daly et al. 2007; Ashcroft & Gollan 2012; Stewart & Nitschke 2017/Chapter 2). This index was calculated as the square root of the difference between the elevation at each target cell and

focal minimum within an 8.76 km circular search diameter. The optimal focal range for the topographic index was systematically assessed by iteratively adjusting the search diameter (1.1 km to 90.2 km) and cross-validating minimum temperature (Appendix 3.B).

Thermal remote sensing data from collection 6 of the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD11A2 (Wan et al. 2015) Land Surface Temperature (LST) product (approx. 1 km cell resolution) was used as an independent covariate for temperature interpolation. The MOD11A2 MODIS product can be effective in improving temperature interpolation (Hengl et al. 2012; Stewart & Nitschke 2017/Chapter 2) as it provides an indirect estimate of land surface temperature and is sensitive to land cover classification (Snyder et al. 1998; Wan 2006). All 8-day composite scenes available between February 2000 and December 2015 were downloaded using the *MODIS* package (Mattiuzzi 2016) in R (R Core Team 2016). Scenes were rejected where visual inspection indicated clear spatial artefacts, or the number of cells with invalid LSTs was greater than 50% across Bhutan. This threshold was set to ensure enough scenes were retained during the summer monsoon, when there is a very high level of cloud cover. Each image was then transformed into z-scores, grouped by month and averaged for each cell location. Outliers falling outside of the 95% confidence interval were excluded when calculating the final mean value at each cell location (Stewart & Nitschke 2017/Chapter 2). Standardised monthly MODIS surfaces were calculated separately for day scenes and night scenes to be used as predictors for interpolation of maximum temperature and minimum temperature, respectively. Due to the extremely cloudy conditions and spatial artefacts noted for several months during visual inspection of the LSTs, clear sky masks from the MOD11A2 product were also used to support the analysis. Daily clear sky images were extracted by converting 8-bit integers in the 8-day composite clear sky data to binary vectors. The mean fraction of clear sky during the day and night was then calculated for each pixel, and as a regional average, for each month.

3.2.3. DATA ANALYSIS

Monthly maximum temperature, minimum temperature, precipitation and vapour pressure climate normals for the 1986–2015 reference period were interpolated using trivariate splines (Wahba 1990; Hutchinson 1995) in ANUSPLIN 4.4 (Hutchinson & Xu 2011). The spline smoothing parameter was estimated using generalised cross-validation (GCV; Craven & Wahba 1979). For each variable, full spline dependence upon latitude, longitude and elevation was assessed. Additional partial dependencies (Bates et al. 1987) were also assessed for both maximum temperature (standardised MODIS day time LST) and minimum temperature (standardised MODIS night time LST, topographic index). The square root of vapour pressure (McKenney et al. 2004) and precipitation (Hutchinson 1995; Hutchinson 1998; Hutchinson 2009) climate normals were used for interpolation and the final predictions were subsequently converted back to units of hectopascals (hPa) and millimetres. ANUSPLIN internally corrects for the small amount of bias that arises as a result of these transformations (Hutchinson & Xu 2011). As site elevations extracted from the smoothed precipitation DEM are a function of the surrounding landscape they may differ from values present in the site metadata (RMSE = 323 m). Precipitation was therefore cross-validated using both the actual and smoothed elevation values to ensure the smoothed interpolation would produce reliable results.

Cross-validation was performed by iteratively leaving out one observation and refitting the model until independent predictions were made for all locations. The coefficient of determination (r^2), mean absolute error (MAE), root mean square error (RMSE), ratio of the RMSE to the standard deviation of the observations (RSR; Moriasi et al. 2007) and mean error (BIAS) were used to assess model performance. Following cross-validation, monthly climate normal surfaces were generated using all available stations for each model.

Residual analyses were performed to investigate the differences in model predictions when using alternative variables for interpolation, and also to compare the surfaces generated in this study against globally representative climate datasets. In order to detect differences in the spatial distribution of model predictions for temperature, residual values were calculated for each partial trivariate spline model by subtracting the trivariate spline with full dependence upon latitude, longitude and elevation. Empirical cumulative distribution plots were used to

investigate the spread of mean annual maximum and minimum temperature residuals. November was selected to illustrate the spatial distribution of minimum temperature residuals.

Mean annual temperature and annual precipitation were extracted from the WorldClim (Hijmans et al. 2005) and the CRU CL 2.0 (New et al. 2002) datasets and compared against the new surfaces generated using the local weather station network. Residuals were calculated by subtracting the WorldClim and CRU surfaces from the gridded datasets generated in this study. Thermal remote sensing data is sensitive to land use type (Snyder et al. 1998; Wan 2006) and therefore partial spline models for temperature using standardised MODIS LST values were not assessed against the WorldClim or CRU datasets to ensure an appropriate comparison.

3.3. RESULTS

Cross-validated statistics for maximum temperature, minimum temperature, vapour pressure and precipitation climate normals are summarised in Table 3.1. All partial spline models for temperature variables provided a performance improvement over the full trivariate spline. Pooled statistics for maximum temperature demonstrate a 7.9% improvement in RMSE over the full trivariate spline when using standardised day time MODIS LST values as an independent covariate. Pooled statistics for minimum temperature demonstrate an improvement of between 10.4% and 12.3% in RMSE when using standardised night time MODIS LST values, the topographic index, or their combination, as independent covariates. The use of smoothed DEM values rather than site elevations provided an 8.8% reduction in RMSE for precipitation. All variables achieved an RSR of 0.3 or less, indicating good model performance. Mean error (BIAS) was negligible for temperature and vapour pressure; however, there was a small negative bias for smoothed precipitation (-5.01 mm) which equated to -0.03% as a proportion of the mean observed value.

Table 3.1: Spatially and temporally pooled cross-validated error statistics for monthly mean (1986 – 2015) maximum temperature, minimum temperature, precipitation and vapour pressure with ordinary and partial trivariate splines. Partial dependencies are indicated in the model suffix (T represents the topographic index; M represents standardised MODIS LST values).

	r^2	MAE	RMSE	RSR	BIAS
Maximum Temperature (°C)					
3DS	0.93	1.15	1.44	0.26	0.03
3DS-M	0.94	1.09	1.33	0.24	0.01
Minimum Temperature (°C)					
3DS	0.95	1.14	1.46	0.23	-0.02
3DS-T	0.96	1.04	1.31	0.20	0.00
3DS-M	0.96	1.03	1.28	0.20	0.00
3DS-TM	0.96	1.03	1.28	0.20	0.00
Precipitation (mm)					
3DS (site elevation)	0.89	0.25 ^a	0.47 ^a	0.34	-0.05 ^a
3DS (smoothed elevation)	0.90	0.22 ^b	0.43 ^b	0.30	-0.03 ^b
Vapour Pressure (hPa)					
3DS	0.96	1.06	1.36	0.20	0.00

r^2 = coefficient of determination, MAE = mean absolute error, RMSE = root mean square error, RSR = ratio of the RMSE to the standard deviation of the observations, BIAS = mean error.

^a precipitation MAE (35.98 mm), RMSE (68.44 mm) and BIAS (-7.52 mm) expressed as a proportion of the mean.

^b precipitation MAE (32.41 mm), RMSE (62.40 mm) and BIAS (-5.01 mm) expressed as a proportion of the mean.

The cross-validated monthly RMSE for all variables and models summarised in Table 3.1 are illustrated in Figure 3.4. The partial trivariate spline for maximum temperature (3DS-M) was effective throughout the year and demonstrated the largest improvement between January and October (4.8% to 16.0% reduction in RMSE) when compared against the full trivariate spline (3DS). Partial spline models for minimum temperature (3DS-T, 3DS-M and 3DS-TM) were most effective in improving performance during the cooler months between October and April; however, they also provided a small improvement in May. Minimum temperature typically performed best during this period when including partial dependence upon both the standardised MODIS values and the topographic index (3DS-TM; 10.4% to 23.4% reduction in RMSE when compared against 3DS). The RMSE of monthly precipitation climate normals cross-validated using the full trivariate spline (3DS) was highest during the wettest months between May and September (RMSE between 55.8 mm and 120.7 mm). The ratio of the RMSE to the mean was relatively stable across this period (29.3% to 37.1%),

suggesting that the high RMSE values are likely due to increased precipitation rather than reduced model performance.

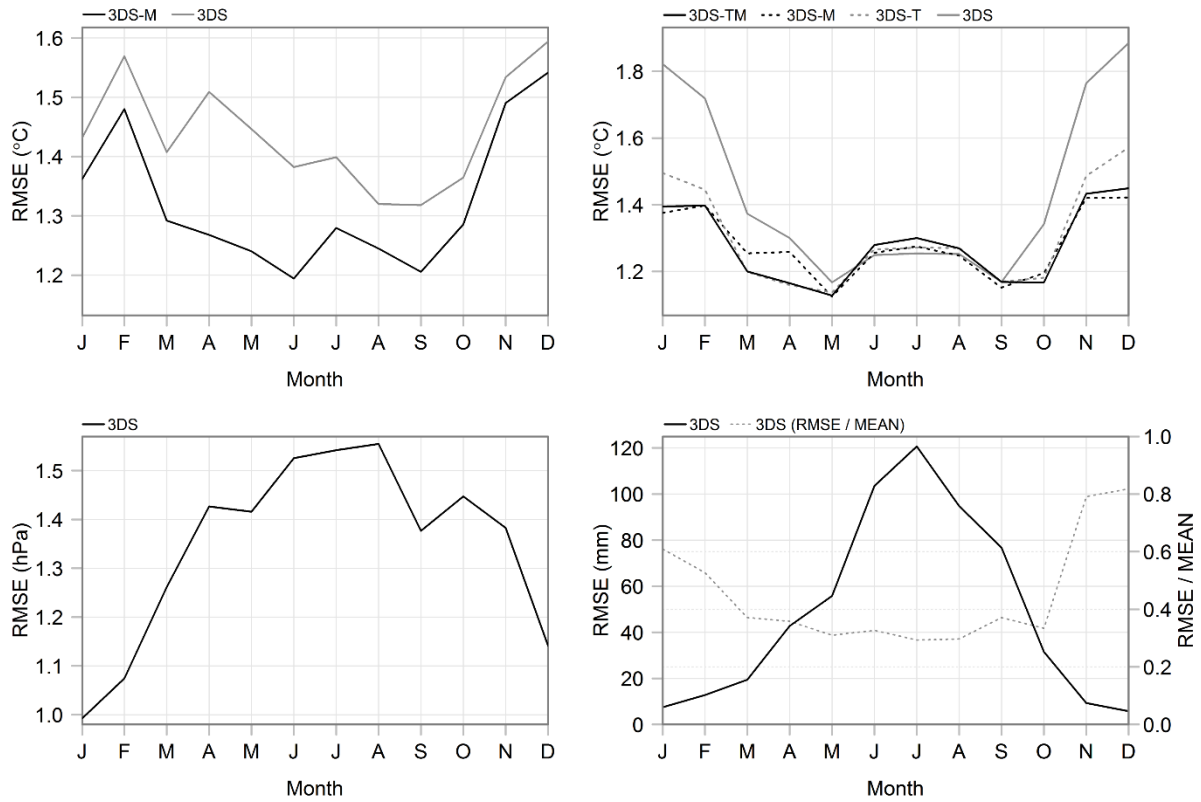


Figure 3.4: Cross-validated RMSE of monthly climate normals (1986 – 2015) for maximum temperature (top left), minimum temperature (top right), vapour pressure (bottom left) and precipitation (bottom right) using ordinary trivariate splines (3DS) and partial trivariate splines (3DS-T, 3DS-M, 3DS-TM). The topographic index (T) and standardised MODIS values (M) are included as partial dependencies where indicated in the model suffix.

Daily MODIS acquisitions show that the fraction of clear sky over Bhutan is lowest during the day between May and September (Figure 3.5). The regional mean vapour pressure is also highest during these months. With the exception of May, partial spline models were ineffective at improving minimum temperature interpolation performance throughout this period when compared against the trivariate spline with full dependence upon latitude, longitude and elevation. The clear sky fraction was on average lower during the night between October and April.

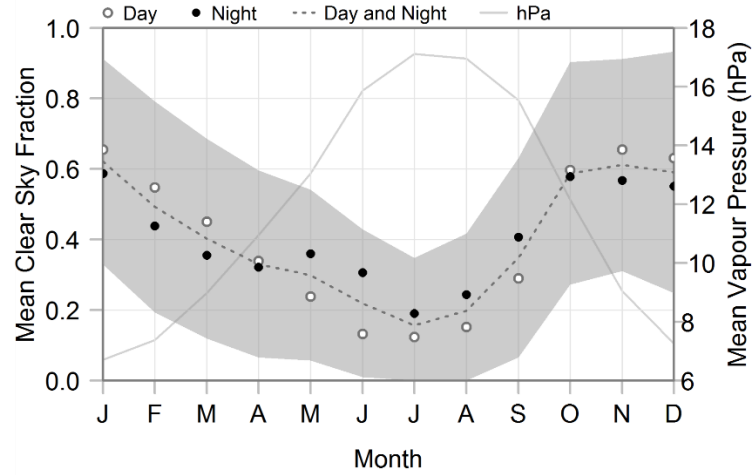


Figure 3.5: Regional monthly mean clear sky fraction (MOD11A2 clear sky days; LP DAAC 2016b) and vapour pressure. Confidence bands represent the mean clear sky fraction (day and night combined) ± 1 standard deviation.

The distribution of mean annual maximum and minimum temperature residuals, calculated by subtracting the full trivariate spline (3DS) from each partial trivariate spline variant (3DS-T, 3DS-M and 3DS-TM), are presented in Figure 3.6. Mean annual maximum temperature residuals (3DS-M) range from -4.2°C to 4.8°C and are cooler than the full trivariate spline across 81.2% of the region. Mean annual minimum temperature residuals (Figure 3.6) demonstrate congruence between the partial trivariate spline models and are warmer across 68.2% of cells for 3DS-T (-2.2°C to 1.9°C), 71.9% of cells for 3DS-M (-2.3°C and 3.0°C), and 73.1% of cells for 3DS-TM (-2.1°C and 2.6°C).

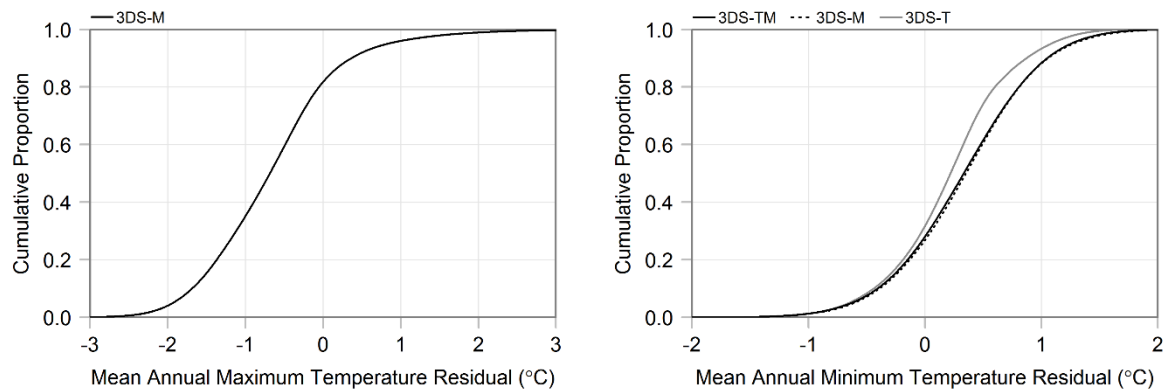


Figure 3.6: Cumulative distribution of mean annual maximum and minimum temperature residuals ($n = 814,914$) calculated by subtracting the ordinary trivariate spline from model variants developed using partial dependencies. The topographic index (T) and standardised MODIS values (M) are used as partial dependencies where indicated in the model suffix. Extreme values are constrained for visual clarity.

Minimum temperature residuals in November (Figure 3.7) show a similar spatial distribution for all models, with a warming of slopes and cooling of areas with low relative elevation. Minimum temperature interpolation using standardised MODIS LST values show a much broader range of values in comparison to variants using only topographic metrics. Residuals were up to 1.8 °C cooler and 1.3 °C warmer for 3DS-TM in comparison to the maximum range predicted by 3DS-T.

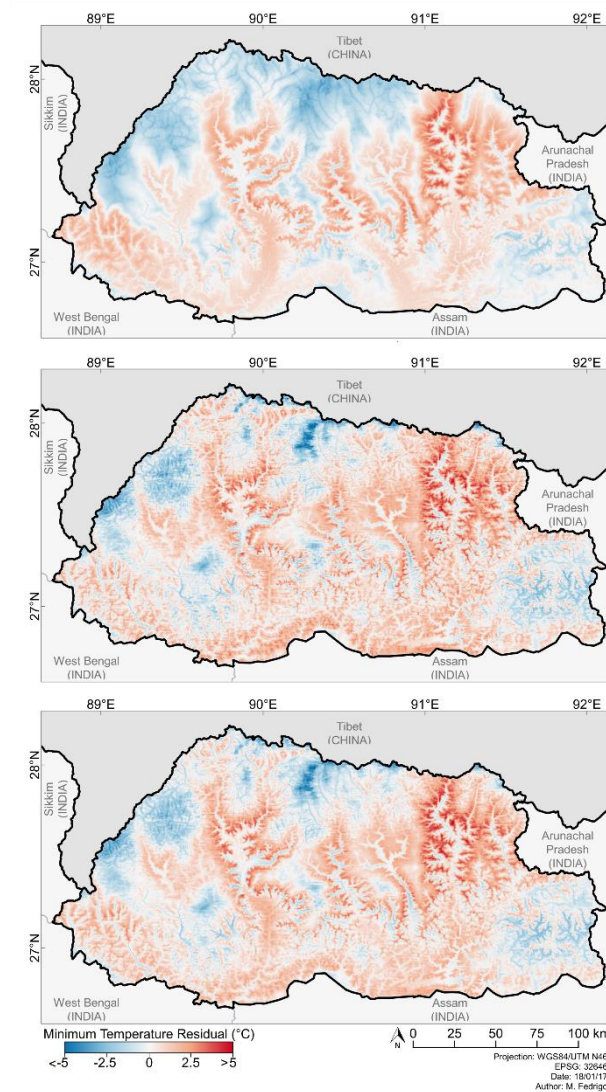


Figure 3.7: November minimum temperature residuals calculated by subtracting the ordinary trivariate spline (3DS) from trivariate splines with partial dependence upon the topographic index (top; 3DS-T), standardised day time MODIS values (middle; 3DS-M), and both the topographic index and standardised day time MODIS values (bottom; 3DS-TM). Extreme residual values have been constrained for visual clarity.

The spatial distribution of mean annual temperature and annual precipitation interpolated using the local weather station network (maximum temperature 3DS; minimum temperature 3DS-T; precipitation 3DS) show large deviations from the WorldClim and CRU CL 2.0 datasets (Figure 3.8). The regional mean annual temperature for locally calibrated interpolations was 0.75 °C warmer than the WorldClim dataset, and 1.81 °C warmer than the CRU dataset. This result was most pronounced across the western regions of Bhutan in the WorldClim dataset. For mean annual temperature, the residuals between the new surfaces and the WorldClim values varied by as much as 5.9 °C and the residuals between the new surfaces and the CRU values varied by up to 12.9 °C. The 3DS model predicts the greatest amount of precipitation across the southern foothills of Bhutan; however, unlike the WorldClim and CRU datasets, these high rainfall regions do not extend into the central valleys. Precipitation residuals show deviations of up to 3,364 mm in the WorldClim dataset, and up to 2,845 mm in the CRU dataset when compared against locally calibrated interpolation. Precipitation typically decreases with elevation across Bhutan in the WorldClim and CRU datasets. The 3DS model exhibits an increase in precipitation with elevation across the central valleys and a decrease in overall precipitation towards the far north of Bhutan.

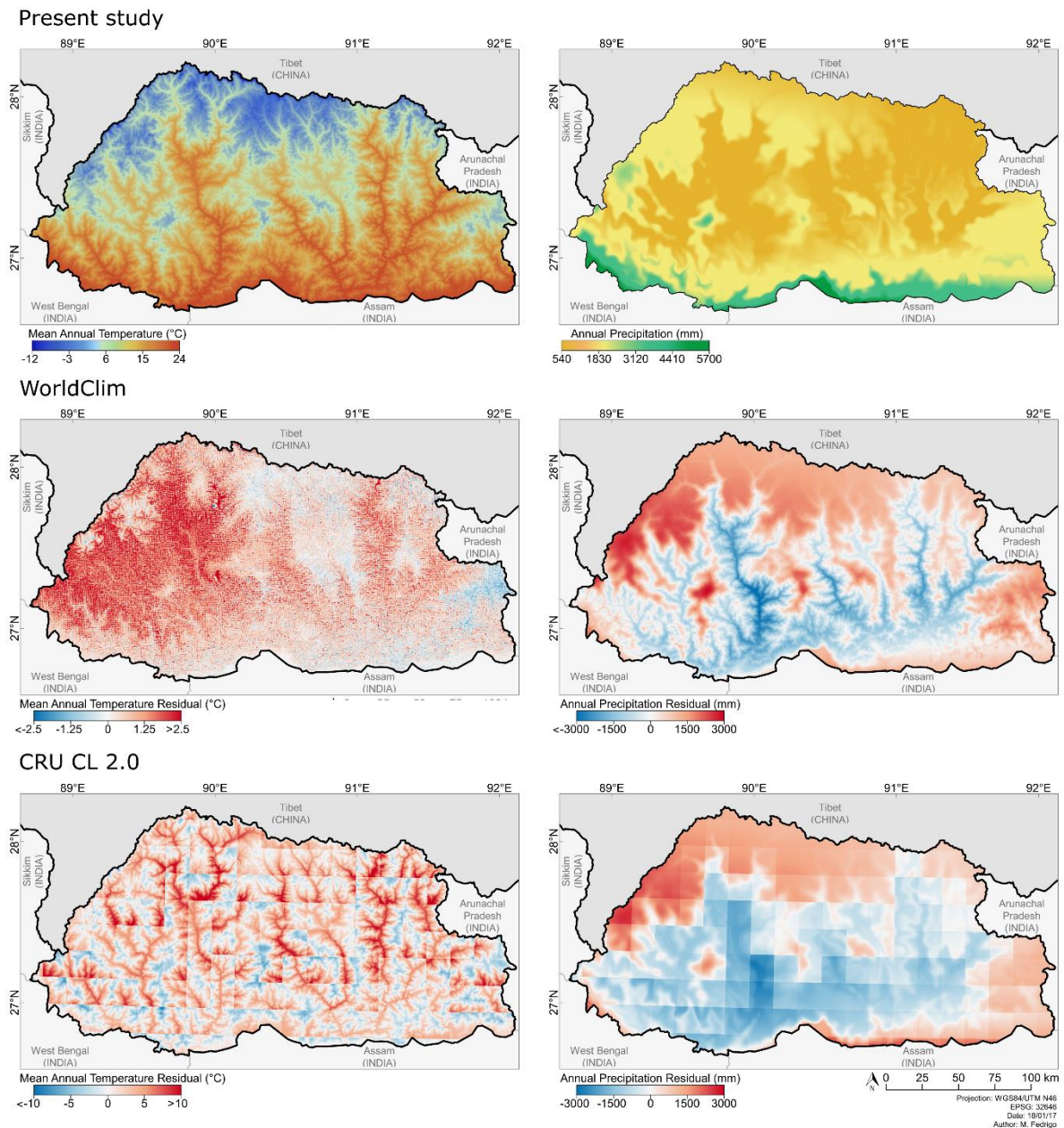


Figure 3.8: Mean annual temperature (top left) and annual precipitation (top right) calculated in the present study (full spline dependence upon latitude, longitude and elevation for maximum temperature and precipitation; additional partial dependence upon the topographic index for minimum temperature) and the spatial distribution of residuals when subtracting the WorldClim dataset (middle row; 1950–2000; Hijmans et al. 2005) and the CRU CL 2.0 dataset (bottom row; 1961–1990; New et al. 2002). Extreme residual values have been constrained for visual clarity.

3.4. DISCUSSION

The results of this study demonstrate the advantages of incorporating MODIS LST data and local topographic indices as additional partial dependencies when interpolating temperature variables across topographically complex landscapes, such as those in Bhutan. Stewart and Nitschke (2017/Chapter 2) found similar outcomes for the effectiveness of these variables in southeast Australia, despite large differences in topographic and climatic conditions. They found that MODIS LST values improved maximum temperature interpolation performance the most during the warm summer months. In Bhutan, the largest improvements in maximum temperature interpolation performance were also achieved during the warmest months when using standardised MODIS LST values as an independent covariate. This performance improvement was maintained throughout the summer monsoon, despite heavy day time cloud cover which reduced the amount of data available to construct standardised surfaces. The MOD11A2 product is sensitive to land cover classification, and therefore the seasonal performance differences may be due to the indirect detection of spatially aggregated microclimatic conditions responding to higher temperatures, particularly during the summer months.

Both the MODIS LST values and local topographic metrics were effective at improving minimum temperature interpolation performance during the dry months between October and May; however, neither provided a performance improvement between June and September. This congruence suggests that MODIS LST data may be particularly effective at detecting temperature inversion signals in the long term climate record, and also indicates that the effectiveness of these variables may be considerably reduced during cloudy, wet and humid conditions that are characteristic of the summer monsoon in Bhutan. The extensive cloud cover observed during these months did not have a negative impact on maximum temperature performance when using MODIS LST values, and therefore the lack of performance improvement for minimum temperatures was likely due to the absence of a detectable inversion effect in the long term record, rather than as a result of poor data quality. The release of latent heat and suppression of outgoing longwave radiation associated with extensive cloud cover, heavy precipitation and high vapour pressure are likely to overcome the influence of temperature inversions and local topography during the wet months of the summer monsoon. These conditions are likely to suppress temperature inversion regimes due to their influence

upon the surface energy balance (Iijima & Shinoda 2000; Whiteman et al. 2007; Barry 2008; Zardi & Whiteman 2013). The nocturnal release of latent heat has also been associated with the persistence of up-slope and up-valley winds in the eastern Himalayas (Ohata et al. 1981; Barry 2008), which may further suppress thermal stratification of air near the surface and the development of cold air flows and pools. Both variables were, however, effective at improving minimum temperature interpolation performance between October and May. When included separately as partial dependencies, each variable led to a warming of slopes and a cooling of valley bottoms when compared against the trivariate spline with full dependence upon latitude, longitude and elevation. This result is consistent with the current understanding of nocturnal temperature distributions in mountainous terrain (Geiger 1965; Whiteman 2000; Barry 2008).

Horizontal scaling of the topographic index resulted in an optimal search diameter of approximately 8.8 km, which is 5 times greater than the optimal diameter identified for southeast Australia (Stewart & Nitschke 2017/Chapter 2). Furthermore, using both MODIS LST data and the topographic index provided an additive improvement in minimum temperature performance in southeast Australia that was not found for Bhutan. This is potentially due to the scale of topographic variation in Bhutan (southeast Australia is comparatively much flatter with small peak-to-peak distances in the alpine regions) and the ability of the MODIS LST data to detect temperature inversions at appropriate scales. These results suggest that a spatially varying dependence upon the topographic index, calculated with short search diameters, in conjunction with MODIS LST data may allow for spatial interpolation of current minimum temperatures at much greater spatial extents. This may prove useful for spatial predictions of current climate; however, thermal remote sensing data is sensitive to land cover and therefore should not be used for projecting climate change scenarios.

When utilising the local weather station network in Bhutan, new precipitation surfaces were able to characterise the heavy rainfall experienced in the southern foothills while retaining the effect of orography on precipitation throughout the central valleys and ranges. Precipitation is suppressed across the interior of these valleys and ranges by strong up-valley and up-slope winds (Whiteman 2000), which can lead to an underestimation of rainfall throughout the central regions of Bhutan (Norbu et al. 2003). Historical rainfall data and the distribution of vegetation suggests that the slopes and ridges throughout these regions are wetter than the inner valleys (Ohsawa 1987; Norbu et al. 2003), which is reflected in the spatial distribution of precipitation predicted in this study. The precipitation surfaces presented should be interpreted

with a degree of caution, as much of the precipitation in the higher elevation regions of Bhutan falls as snow and elevations above 3,537 m asl are not represented by the local weather station network. Furthermore, precipitation is highly variable in the southern foothills of Bhutan and the representativeness of mean conditions is therefore dependent upon the available data series length.

The importance of spatial resolution and observation density is apparent when comparing the datasets developed as part of this study against globally consistent climate datasets such as WorldClim and CRU CL 2.0. Analyses of the CRU CL 2.0 residuals show that the within-cell mean annual temperature variability can be as high as 20 °C for coarse resolution products in Bhutan. While downscaling approaches are an option, they cannot incorporate the effects of mesoscale processes such as temperature inversions. The temperature bias that is evident in the WorldClim residuals across western Bhutan, where temperatures are often at least 2.5 °C cooler than predicted in the present study, indicate the importance of observation density and placement. It is unlikely that this region has experienced such an increase in mean annual temperature given that the datasets compared are centred on reference periods that differ by only 25 years. The analyses of precipitation residuals show extreme deviations between the present study and both the WorldClim and CRU CL 2.0 datasets. These results support conclusions by Hijmans (et al. 2005) that station density is perhaps the most important factor for inferring the quality of interpolated climate datasets. Station observations that qualify for inclusion in global databases may be limited in many cases due to data and weather station availability, insufficient length of records, or lack of quality control processes. When globally representative surfaces such as WorldClim are used for regional studies, an evaluation of point density and topographic variability is recommended to evaluate whether or not these surfaces are likely to capture climatological processes at appropriate scales. Acquisition and interpolation of regional weather station data may be justified, and in some cases required, where the point density is too low.

The temperature and vapour pressure surfaces generated as part of this study allow for the spatial estimation of vapour pressure deficit and relative humidity. These variables can be critical for modelling vegetation distributions, as they characterise the atmospheric demand for moisture. While outside the scope of the present study, vapour pressure surfaces may also be used for atmospheric attenuation when modelling potential incoming solar radiation (e.g. Böhner & AntoniĆ 2009; Conrad et al. 2015). Vapour pressure precludes the need for estimates

of lumped atmospheric transmittance, and allows for the effects of elevation to be incorporated into solar radiation predictions. Solar radiation modelling in Bhutan is, however, likely to be complicated by heavy cloud cover, particularly during the summer monsoon. Observations of sunlight hours are available at a small number of stations within the local weather station network in Bhutan, which may facilitate the production of high quality solar radiation surfaces in the future.

3.5. CONCLUSION

The datasets presented in this paper provide a new resource for ecological and agricultural research in Bhutan. Alternative versions of temperature variables were generated to provide the highest quality surfaces (MODIS LST variants) and to maximise compatibility with climate change projections (topographic index). These temperature datasets are calibrated specifically for Bhutan using the local weather station network, are sensitive to the climatic conditions present during the summer monsoon, and incorporate inversion signals that cannot be detected using existing methodologies for statistical downscaling. Both the topographic index and the standardised night time MODIS LST values show evidence that they can detect the effects of temperature inversions on minimum temperature climate normals. These particular covariates are rarely used to improve temperature interpolation, and therefore their application is novel for the region. Precipitation surfaces characterise the heavy precipitation observed in the southern foothills, while retaining the effects of orography throughout the central regions of Bhutan. These effects are absent from global climate surfaces as they do not include weather station observations from within Bhutan. Incorporating the effect of orography on precipitation using trivariate spline interpolation provides a large improvement over polynomial regression techniques that have previously been applied in Bhutan. Globally representative humidity data is very coarse in resolution. The inclusion of vapour pressure surfaces allows for the calculation of humidity metrics and vapour pressure deficit, which will further facilitate ecological modelling and assist in decision making for climate change adaptation throughout Bhutan.

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3.7. APPENDICES

APPENDIX 3.A: CALIBRATION OF PRECIPITATION DIGITAL ELEVATION MODEL

The standard deviation of the Gaussian filter (search diameter of 7.8 km) used to smooth elevation was determined by cross-validating precipitation (leave-one-out) climate normals in Bhutan. The square root of precipitation was interpolated using trivariate splines (full spline dependence upon latitude, longitude and elevation), and final predictions were back transformed to units of millimetres. Performance began to decrease as the standard deviation of the filter exceeded 10 cells (Figure 3.A.1). Any level of smoothing provided a performance improvement over the use of raw site elevations (68.4 mm; 7.4% to 8.8% reduction in RMSE); however, there was little difference between each level of smoothing (maximum difference of 1.5% in RMSE).

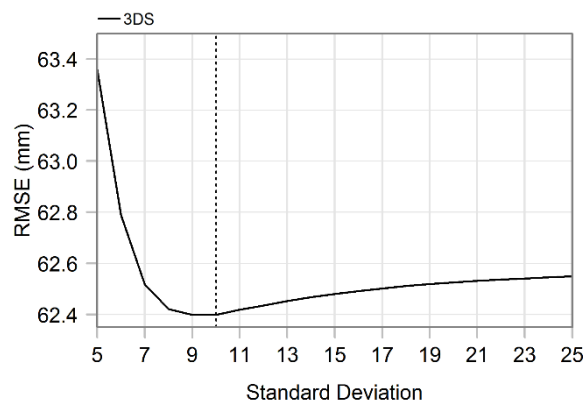


Figure 3.A.1: Spatially and temporally pooled cross-validated RMSE for precipitation interpolated using varying Gaussian filter standard deviations (5 to 25) to smooth the DEM.

APPENDIX 3.B: CALIBRATION OF TOPOGRAPHIC INDEX FOR MINIMUM TEMPERATURE

The optimal search radius for the topographic index of relative elevation was determined by cross-validating minimum temperature (leave-one-out) climate normals in Bhutan. Minimum temperature was interpolated using trivariate splines (spline dependence upon latitude, longitude and elevation) with partial dependencies upon the topographic index (T) and standardised night time MODIS LST values (M). The optimal search diameter for the 3DS-T variant is 8.8 km. The 3DS-TM variant showed much less variability and also experiences a dip (comparatively) at 8.8 km (Figure 3.B.1). This dip is likely caused by the difference in spatial resolution between the DEM (approx. 225 m resolution) and the MODIS data (approx. 1 km resolution). The relative elevation predictor provides additional information that is available within the effective cell resolution of the MODIS data. The dip at 8.8 km also observed for the 3DS-TM is therefore likely to be driven by the relative elevation predictor variable and variability that occurs at sub-MODIS pixel scales. Slightly lower RMSE values are found at a diameter of 30 km to 40 km; however, the differences are negligible.

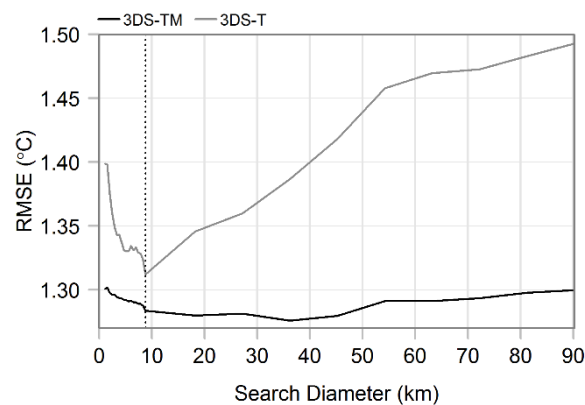


Figure 3.B.1: Spatially and temporally cross-validated RMSE for minimum temperature interpolated using topographic search indices of varying search diameters (1.1 km – 90.2 km). Standardised night time MODIS LST values (M) and the topographic index (T) are indicated in the model suffix where used as partial spline dependencies.

4

CHAPTER FOUR: EVALUATING TEMPORAL VARIABILITY IN CLIMATE FOR PREDICTING PLANT SPECIES DISTRIBUTIONS

This chapter explores the temporal characteristics of climate and how it influences the predicted distribution of plant species. Precipitation, vapour pressure and evapotranspiration datasets were generated at high spatial and temporal resolutions across Victoria to complement the temperature datasets previously developed in Chapter 2. Extreme value theory was used as a basis for generating climate variables for Victoria that characterise interannual trends at fine spatial scales relative to contemporary alternatives in the region and capture the skewed distribution of extreme series. Responses to the magnitude and expected frequency of climate extremes are assessed for 37 plant species across Victoria.

4.1. INTRODUCTION

Ecological models link the responses (e.g. abundance, growth rates, fecundity) and spatial patterns (e.g. occurrence, extent) of organisms to changes in environmental conditions (e.g. climate, soils, landform, vegetation structure, etc.). Environmental envelope models (Nix 1986; Booth et al. 2014; Booth 2018), correlative models driven by statistical inference (Elith & Leathwick 2009) and mechanistic (or process-based) models which rely upon a detailed pre-existing knowledge of complex biophysical processes (Kearney & Porter 2009; Mok et al. 2012) are used to model species distributions. Correlative models are commonly used as they are adaptive to the response of interest, flexible to the predictors used to characterise environmental conditions and can have predictive performance comparable with more complex mechanistic models when suitably calibrated (Kearney et al. 2010; Briscoe et al. 2016). Correlative models can be a useful tool for understanding factors which shape a species distribution and how this range may change over time (Guisan & Zimmerman 2000; Elith & Leathwick 2009). While a diversity of allogenic, autogenic and biogenic processes influence

biological systems, climate and weather are dominant drivers of species distributions (Woodward & Williams 1987; Huntley et al. 1995; Suggitt et al. 2017) and are essential to ecological models.

Many species distribution models rely upon long term averages of bioclimatic variables as spatial covariates (Booth et al. 2014; Booth 2018), though extreme indices (e.g. percentiles, count of days above or below a threshold temperature) have become more common in recent years (e.g. Briscoe et al. 2016; Morán-Ordóñez et al. 2018). Long-term averages in climate and their derived indices, however, may not represent the influence that climate variability can have on key biophysical processes that alter vital rates (e.g. growth rates, fecundity) and thereby shape a species distribution (Mok et al. 2012; Briscoe et al. 2016; Reyer et al. 2017). The availability (or lack-thereof) of climate data at ecologically meaningful spatial scales and the well-established practice of using bioclimatic variables for species distribution modelling has led to the widespread use of WorldClim datasets (Hijmans et al. 2005; Fick & Hijmans 2017). These datasets are freely accessible, require minimal pre-processing (bioclimatic variables are pre-computed) and represent global land surface areas at relatively high resolution of 0.008°. A significant limitation, however, is that these datasets only reflect long term average conditions and as a result can be used to estimate intra-annual variability (i.e. seasonality) but not interannual variability. Global time series climate datasets such as those developed by the Climatic Research Unit (CRU; Harris et al. 2014) can estimate interannual variability but tend to be much coarser in spatial resolution (0.5° grids). This trade-off between spatial and temporal resolution is common for openly available climate datasets. While previous research has highlighted the potential importance of spatial grain on model predictions (Franklin et al. 2013; Guisan et al. 2007), particularly in topographically complex terrain, it is not surprising that temporal resolution and variability have not been thoroughly investigated given constraints around obtaining or generating suitable climate data. Furthermore, even when time series data is available, there are an immense number of ways in which meteorological parameters can be expressed and summarised across multiple variables.

Several studies have successfully demonstrated that weather and extreme events influence habitat suitability for organisms that are able to adjust their distributions and abundances in response to environmental conditions. Reside et al. (2010) found that short-term weather data could better explain bird distributions than climate for nomadic populations in desert regions of Australia, and that long-term averages would have otherwise overestimated

their predicted range. Bateman et al. (2012) found that bettong (*Bettongia tropica* and *Aepyprymnus rufescens*) observations modelled using weather as opposed to long term means better described species ecology and could assist in explaining the niche separation between two species in competition. Two subsequent studies on birds (Bateman et al. 2015) and fish (Pennino et al. 2019) have also demonstrated that considering temporal variability can improve correlative models and better explain ecological dynamics. While these approaches have been effective for mobile organisms, plant species are unable to migrate in response to weather or extreme events. The static nature of plants and influence of stabilising processes which can counteract extreme events (Lloret et al. 2011) suggests that their persistence may be more responsive to the distribution of extremes, rather than specific events. This is supported by Rypkema et al. (2019) who found that the growth rates of an understorey shrub were responsive to the frequency and magnitude of storm damage. The study by Zimmerman et al. (2009) remains one of the few attempts to use variables representing interannual variability in climate for correlative analyses of plant distributions. They found that incorporating the interannual standard deviation of winter temperatures and a summer moisture index, in conjunction with seasonal means provided a small but consistent improvement in model performance. Furthermore, predictions were most influenced by interannual variability at species' range limits, indicating that climatic extremes may be important for characterising source-sink dynamics (i.e. growth or decline in populations with fluctuations in environmental conditions; Pulliam 1988) in correlative models. The ability to concisely summarise interannual variability in extremes is therefore essential for developing simple sets of predictors that will support model parsimony while characterising an important component of the climatic niche which is not reflected in long term averages.

A disconnect between changes in the mean and variability of extremes is expected under climate change (Katz & Brown 1992; Orlowsky & Senviratne 2012), which highlights the importance of understanding how the statistical properties of time series data can provide insights into ecological dynamics. Correlative analyses of climate change scenarios have historically focused on changes in means, but the projected impacts of climate change involve not only shifts in the central tendency of meteorological parameters, but also increases in the frequency and severity of extreme weather events (Rahmstorf & Coumou 2011; Diffenbaugh et al. 2017; Mann et al. 2017). Evidence for these shifts in the mean, variability and symmetry of ecologically important meteorological variables such as temperature and precipitation have already been observed (Easterling et al. 2000; Rahmstorf & Coumou 2011; IPCC 2014;

Diffenbaugh et al. 2017; Mann et al. 2017; Ummenhofer & Meehl 2017). While complex interdependencies between ecosystem function and factors such as disturbance, dispersal ability, local adaptation, and biotic interactions are critical to anticipating future scenarios (Franklin 2010; Serra-Diaz & Franklin 2019), temporal climate dynamics and extreme events are well understood to be major drivers of change (Gutschick & BassiriRad 2003; Maxwell et al. 2019). Despite this understanding, there are many ways that extremes may be quantified. Identifying how best to quantify the properties of extremes for ecological modelling applications remains both a challenge and an opportunity (Suggit et al. 2017, Soafer et al. 2017).

One approach that has been widely applied in the fields of engineering, finance, hydrology and climatology is the use of the Generalised Extreme Value (GEV) family of distributions (Fisher & Tippet 1928; Coles 2001). The GEV distributions are derived from extreme value theory (EVT; Fisher & Tippet 1928) and are used to evaluate the expected return intervals of rare events by quantifying the probability distribution of extremes. GEV allows for both frequency and magnitude of extreme events to be considered simultaneously which is important as they can influence vital rates (Rypkema et al. 2019) that can lead to changes in the abundances and distributions of species (Parmesan et al. 2000). Despite the potential utility of these methods for representing the magnitude and frequency of extreme events on key ecological processes they have not commonly been applied in ecology (Gaines & Denny 1993; Katz et al. 2005; Denny et al. 2009; Batt et al. 2017; Rypkema et al. 2019).

The objectives of this study were to evaluate climate extreme variables, derived from EVT, as predictors of plant species distributions across southeast Australia. We developed climate variables using GEV distributions that are suited to the statistical properties of extremes and thus can reflect the expected frequency of events that are hotter, colder and / or dryer than typically expected. Our approach builds upon the work of Zimmerman et al. (2009) by evaluating how measures of interannual variability in climate extremes can shape the distributions of plant species.

4.2. METHOD

4.2.1. STUDY EXTENT

Species distribution models were developed for select vascular plant species for the State of Victoria (141°-150°E, 34°-39°S), southeast Australia. Elevations range from sea level to over 1,980 m above sea level in the alpine regions located to the northeast of Melbourne (144.96°E, 37.81°S). The alpine regions commonly experience mean annual temperatures (MAT) of 10 °C or below and mean annual precipitation (MAP) of more than 1,400 mm, with seasonal snowfall occurring at the highest elevations. The western regions of the state are typically much flatter, hotter (MAT up to 18 °C) and dryer (MAP of 600 mm or less) than the heavily forested and topographically complex areas in the east (Stewart & Nitschke 2017/Chapter 2).

4.2.2. SPECIES PRESENCE, ABSENCE AND OCCURRENCE DATASETS

Comprehensive vegetation surveys at 1,864 sites were collated from a range of research studies conducted in forested sites across Victoria between 2006 and 2017 (see Appendix 4.A for details). Surveys from the Victorian Forest Monitoring Program (Haywood et al. 2017) provided a large, systematically sampled, state-wide dataset representing a broad range of environmental conditions and plant species. The remaining datasets were typically focused on specific, but distinct, forested regions across the state. All records were aggregated to the species level as part of the data cleaning procedure, as sub-species were not indicated in many entries. Only one species (*Acacia verticillata*) selected for modelling included more than one subspecies (*Acacia verticillata* subsp. *verticillata* and *Acacia verticillata* subsp. *ovoidea*), each of which share a similar distribution (<https://vicflora.rbg.vic.gov.au/>). Sites were combined where they shared the same pixel in the prediction surfaces to minimise clustering of survey locations and the potential for associated pseudo-replication effects (Hurlbert 1984). Of the 1,900 species recorded across all datasets, 37 vascular plants capable of reaching at least 3 m in height, representing a range of climatic conditions and each having at least 80 presence records available were selected for modelling. These criteria were selected to maximise the probability of detection and to ensure enough presence records for modelling across differing environmental conditions.

4.2.3. CLIMATE DATASETS AND VARIABLE SELECTION

High resolution (approx. 250 m) climate datasets (Stewart & Nitschke 2017/Chapter 2) specifically developed for ecological modelling across Victoria were used to derive surfaces of seasonal extremes (Table 4.1). Aside from spatial resolution, the temperature datasets differ from those typically available for the region by incorporating partial dependence upon thermal remote sensing data and a topographic index of relative elevation to characterise nocturnal cold air drainage, pooling and inversion regimes across the landscape. Remote sensing data can provide better interpolation performance in regions where weather station observations are sparse (e.g. alpine regions of Victoria). A simple moisture index was calculated in a 90-day moving window to characterise cumulative seasonal water availability. Further details on how these datasets were developed and the associated cross-validation statistics are provided in Appendix 4.B.

Table 4.1: Climate datasets used to calculate variables for modelling species distributions.

Variable	Spatial resolution (arc-seconds)	Temporal resolution	Date range	Data source
Minimum temperature	9	Daily	Jan 1981 – Jul 2014	Stewart & Nitschke 2017
Maximum temperature	9	Daily	Jan 1981 – Jul 2014	Stewart & Nitschke 2017
Moisture index ^a	9	Daily	Jul 1990 – Jul 2014	Calculated

^a Moisture index = $P - ET_0$; where P = daily precipitation and ET_0 = daily Penman-Monteith reference evapotranspiration, each aggregated in a lagged 90-day moving window.

A range of climate variables were initially assessed to enable a systematic approach for evaluating climate extremes as predictors of species distributions. Extreme indices were initially considered but were subsequently excluded for reasons including strong collinearity with one another, clear spatial artefacts, or overly smooth spatial distributions (see Appendix 4.C for a more detailed discussion). Furthermore, these indices tend to represent moderate severity extremes with short return intervals, and do not reflect the rarest events (Wang et al. 2013). Most commonly used and pre-existing metrics were therefore not appropriate given our objective of developing variables that represent the interannual temporal dynamics (i.e. expected frequency and magnitude) of climate extremes at multi-decadal timescales.

Climate extreme variables were calculated by fitting GEV distributions (see Coles 2001) to our climate datasets, aggregated to monthly values, using the extRemes package (Gilleland & Katz 2016) in R (R Core Team 2019). This allowed us to characterise both the magnitude and expected frequency of extremes by extracting values at different expected return intervals as given by the fitted GEV distribution. Monthly values were selected for simplicity, as daily percentiles tended to produce spatial artefacts with increasing rarity and were not temporally contiguous. Subsequent testing with weekly extremes calculated in a moving window appeared very similar to and were highly correlated ($r > 0.99$) with, the monthly equivalents and therefore were not considered further. The data processing steps for fitting GEV distributions to monthly time series at a single site are illustrated in Figure 4.1.

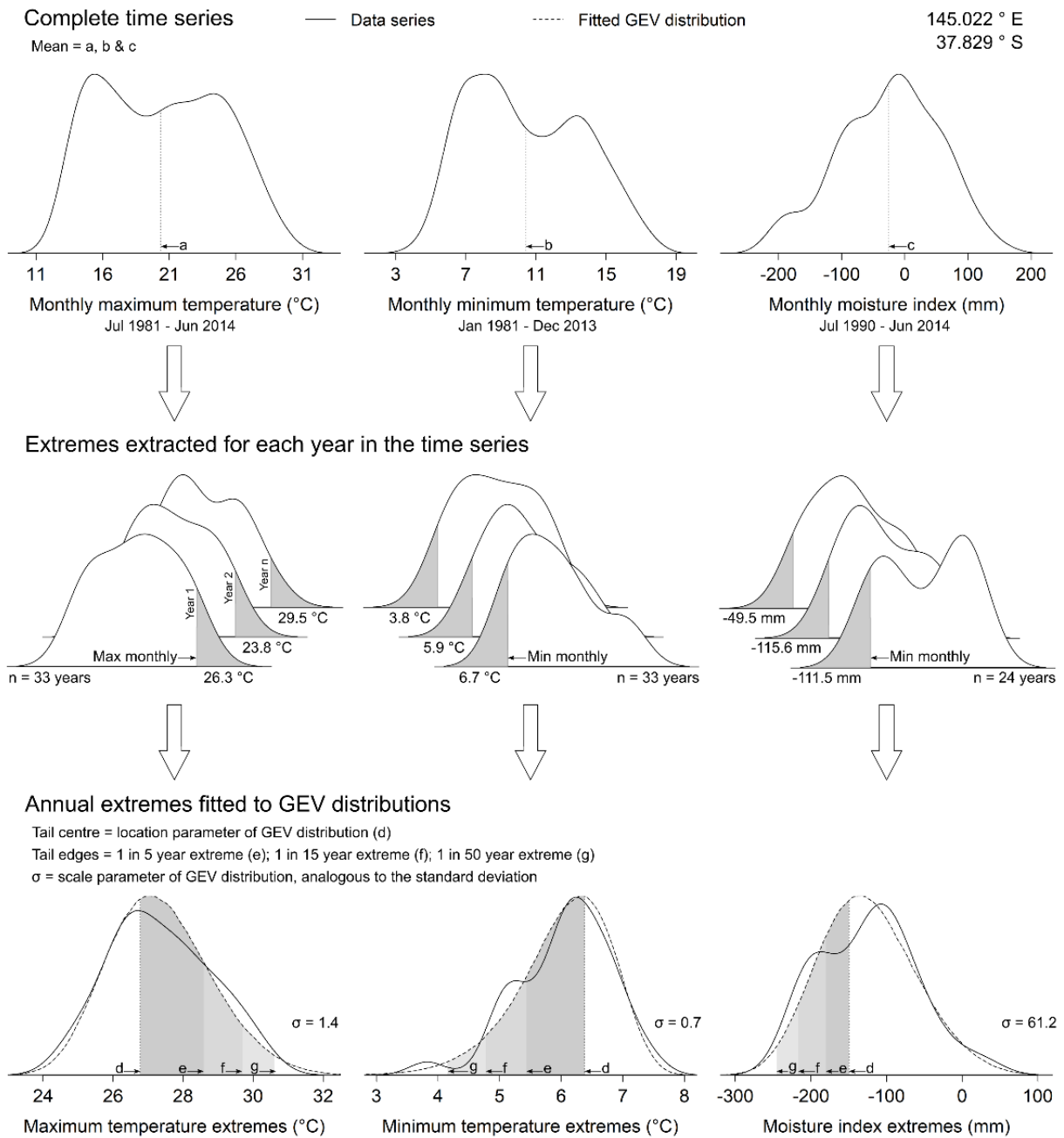


Figure 4.1: Generalised Extreme Value (GEV) distributions fitted to annual maximum temperature, minimum temperature and moisture index extremes at a single site located approximately 7 km east of Melbourne, Australia.

Species distribution models were fitted using 12 different sets of predictor variables (Table 4.2). The tail centre (the location parameter of the GEV distribution, analogous to the mean) of monthly climate extremes (MEX) were fitted and compared against models with the addition of symmetrical ($MEX\sigma$) or asymmetrical ($MEXn$) measures of variability to evaluate additive improvements in performance. The scale parameter of the GEV distribution (analogous to the standard deviation) was used as a uniform, symmetrical measure of variability around the tail centre (for $MEX\sigma$). As the monthly climate extreme variables (i.e. at the tail centre) were highly correlated with the tail edges (i.e. points on the GEV distribution corresponding to extremes of higher magnitude and decreased frequency), asymmetrical measures of variability (for $MEXn$) reflecting skew in the fitted GEV distribution were calculated as:

$$V_n = TE_n - TC$$

where V_n is the calculated variability for expected return interval of n years, TE_n is the tail edge representing an expected return interval of n years, and TC is the tail centre. This formulation minimised collinearity and allowed for the variability component to be isolated and expressed in a way that reflects the skewed distribution of seasonal extremes. Predictor sets were generated to test extremes of increasing magnitude and decreasing frequency at expected return intervals of between 5 and 50 years, in 5-year increments.

Table 4.2: Alternate sets of climate predictor variables used for predicting species distributions. All variables calculated using monthly maximum temperature (MAXT; July 1981 – June 2014), minimum temperature (MINT; January 1981 – December 2013) and moisture index (MI; July 1990 – June 2014).

Set	Climate variables	n variables
MEX	Tail centre of climate extremes (GEV distribution fitted to annual maximum monthly MAXT, and annual minimum monthly MINT and MI).	3
$MEX\sigma$	Tail centre of climate extremes with a symmetric variability (scale parameter of the GEV distribution).	6
$MEXn$	Tail centre of climate extremes with asymmetric variability of extremes (tail centre – tail edge) corresponding to extremes of increasing magnitude and decreasing frequency of one event per n years ($n = 5, 10, \dots, 50$).	6

Tail centre = location parameter of the Generalised Extreme Value (GEV) distribution; tail edge = percentile of the GEV distribution corresponding to expected return interval of n years.

4.2.4. SPECIES DISTRIBUTION MODELLING AND DATA ANALYSIS

Distribution models for 37 plant species were fitted with boosted regression trees (see Elith et al. 2008) using the `gbm.step` function (with dependencies upon the `gbm` package by Ridgeway 2017) of the `dismo` package (Hijmans et al. 2017) in R. Models were fitted with a learning rate of 0.001, tree complexity of 5 and a bag fraction of 0.75, which ensured that the final models contained sufficient trees (>1,000) for stable predictions. The relative contribution of each variable was extracted from each model and illustrated in a boxplot for each species using the `MEXn` model achieving the highest cross-validated D^2 . The most important variable interactions were extracted from each model using the `gbm.interactions` function of `dismo`. Two smoothed perspective plots of the strongest and clearest interactions for each variable were used to illustrate interaction effects between typical seasonal extremes and their variability. Model performance was assessed using the area under the receiver operating characteristic (AUC) and the proportion of deviance explained (D^2) on data held out for cross-validation.

A spatially blocked k-fold cross-validation design was used to ensure a robust analysis of model performance (minimising underestimation of prediction error linked to spatial autocorrelation) that better reflects ability of models to extrapolate into new space (Roberts et al. 2016; Valavi et al. 2018). Spatial blocks were assigned using the `blockCV` package (Valavi et al. 2018) in R. The target block size was selected according to autocorrelation range by fitting variogram models to prediction surfaces and also to the binary presence and absence points themselves. A block size of 1° (approx. $100 \text{ km} \times 100 \text{ km}$) was selected as this was the autocorrelation range indicated by analysis of the prediction surfaces, and at the upper limit of autocorrelation ranges determined for presence and absence points. Presence and absence points were split into test and training sets across 4 to 8 folds using `blockCV`, adjusting the latitude and longitude offsets as required to achieve the most balanced prevalence rate possible for each species. A random 10-fold cross-validation was also run to provide an estimate of interpolation error to allow for a more direct comparison with Zimmerman et al. (2009). Cross-validation blocks (both spatial and randomly selected) were fixed for each species so that alternate variable sets were assessed using the same testing and training groups. All performance statistics presented are derived from the spatially blocked k-fold cross-validation unless otherwise specified.

Cross-validation statistics for MEX σ and all MEX n variants were expressed relative to MEX for each species and illustrated using boxplots. The species that achieved the largest improvement in D^2 with MEX n predictors was selected to illustrate differences in the spatial distribution of predicted probabilities for the different variable sets. Victoria-wide maps of all models fitted with increasing severity and decreasing frequency of extremes (i.e. all MEX n variants) for each species were converted into animated gifs and are provided as supplementary materials. Two species and subset regions were selected to illustrate how the mapped probabilities change with increasing return intervals. Statistical comparisons of model performance were conducted using two-sided Welch's t-tests with p values adjusted for multiple comparisons using the method of Holm (1979). All statistical analyses were performed in R.

4.3. RESULTS

Spatially blocked cross-validated model performance metrics (D^2) for each species, when fitted using the MEX n or MEX σ predictors relative to MEX, are illustrated in Figure 4.2. The MEX σ models achieved D^2 values below, within, and above the range of MEX n results 19, 14 and 4 times, respectively. The median MEX n result was higher than MEX for 28 of 37 species, 22 of which were statistically significant ($p < 0.05$). AUC statistics were mostly consistent with trends in D^2 performance, with 17 of the 22 models achieving a significant improvement in AUC (Appendix 4.E). While *Banksia marginata* and *Coprosma quadrifida* were not statistically significant after adjusting for multiple comparisons, all but two results for these two species (MEX σ and MEX5 for *B. marginata*) had a higher D^2 than MEX. Only 6 of 37 species showed a statistically significant decrease in D^2 relative to MEX, although the difference for *Hedycarya angustifolia* was very small, half of the species achieved better results than MEX at least once, and only 4 species had corresponding significant decreases in AUC. There were 9 species where no significant difference in D^2 was achieved; however, *Eucalyptus nitens* (26) and *Olearia lirata* (27) trended towards an increase, and *Polyscias sambucifolia* (30) and *Eucalyptus goniocalyx* (32) trended towards a decrease relative to MEX. Results of the MEX, MEX σ and MEX n variants achieving the highest D^2 are tabulated for each species in Appendix 4.F with corresponding presence, absence, and cross-validation fold counts.

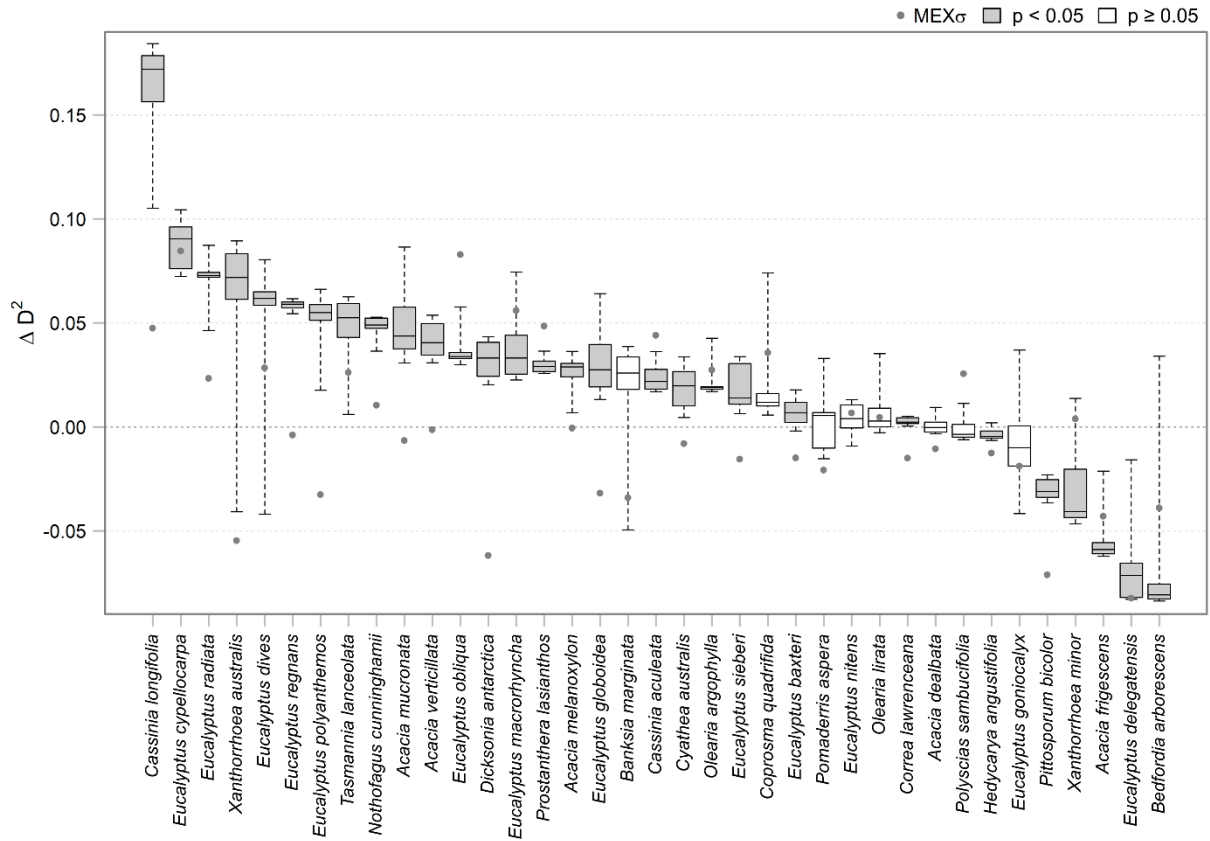


Figure 4.2: Cross-validated change in the proportion of deviance explained for SDMs fitted with extremes and alternate corresponding measures of variability for 37 species. Results are expressed relative to typical monthly extremes (MEX). Boxplots (box corresponds to interquartile range, whiskers to data extremes) show results for models using asymmetric measures of variability derived from extremes of increased magnitude and decreased frequency corresponding to return intervals of between 5 and 50 years. Points correspond to models using symmetric measures of variability (scale parameter of the GEV distribution).

Pairwise performance comparisons of the MEX models with each of the variants incorporating measures of variability are illustrated in Figure 4.3. Significant improvements in cross-validated D^2 and AUC were achieved when the skewed distribution of extremes was used as a measure of variability ($MEXn$). This result was consistent across all tested return intervals for both D^2 and AUC (Figure 4.3), although the difference in AUC for MEX5 was only marginally significant ($p = 0.078$) for the spatially blocked design, and return intervals corresponding to the optimal model performance varied from species to species. Symmetric representations of extreme variability ($MEX\sigma$) did not show a significant difference from typical seasonal extremes when cross-validated using spatial blocks. A near universal performance improvement was achieved under the randomly sampled cross-validation design.

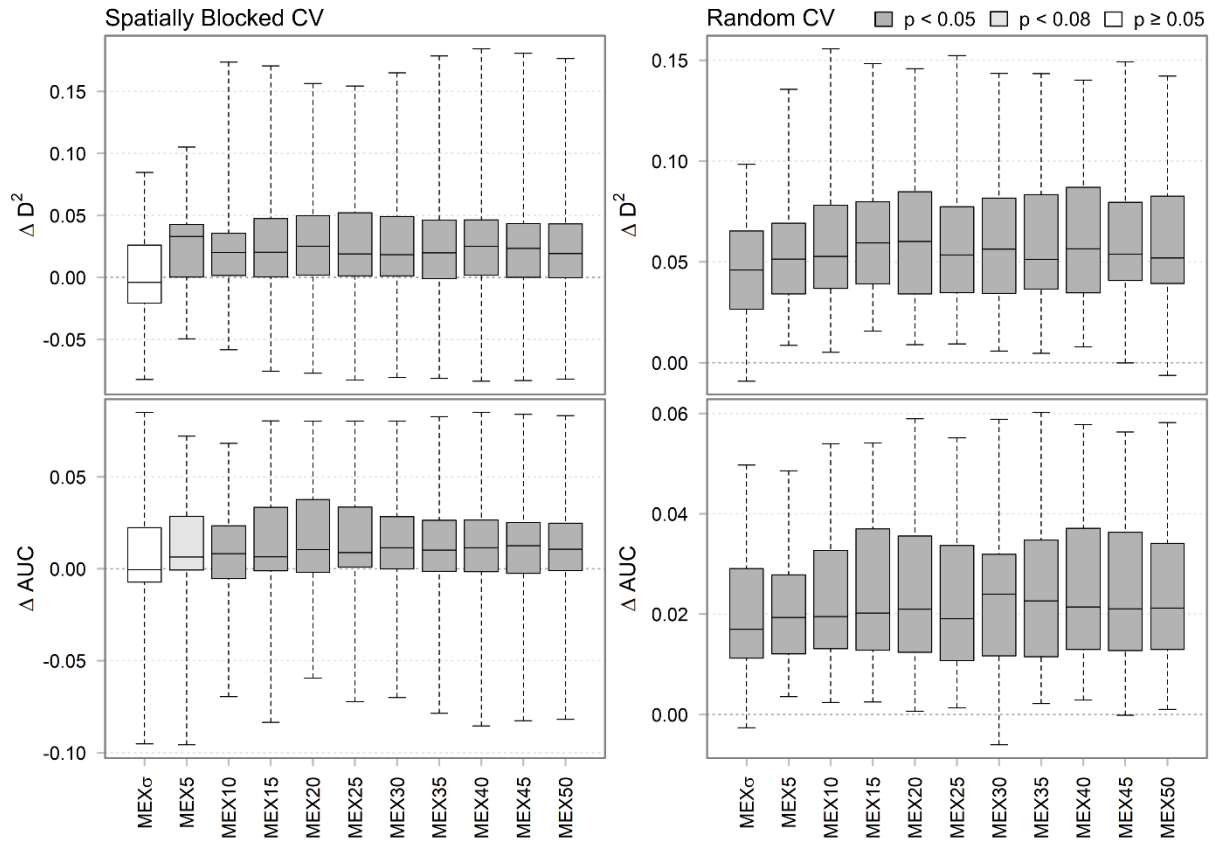


Figure 4.3: Pairwise comparisons of spatially blocked and random cross-validation performance for species distributions ($n = 37$) modelled using extremes and asymmetric (MEX n , where $n = 5, 10, \dots, 50$ years) or symmetric variability (MEX σ) relative to extremes alone. Box corresponds to interquartile range, whiskers to data extremes.

The moisture index was typically the most important extreme predictor, followed by maximum temperature and minimum temperature for species distribution models fitted using MEX n variables (Figure 4.4). Typical seasonal extremes in the moisture index were significantly different than asymmetric variability (MI-V n). While the typical extremes of maximum and minimum temperature were generally higher, there was no significant difference between corresponding measures of variability for either variable. Species responses and the relative contribution of variables for each species are provided in Appendix 4.G.

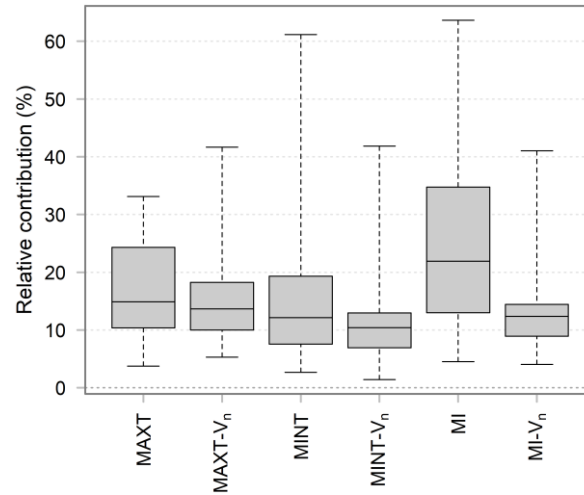


Figure 4.4: Relative contribution of maximum temperature (MAXT), minimum temperature (MINT), moisture index (MI) extremes and corresponding asymmetric variability of extremes (V_n ; where n = expected return interval in years) to species distribution models fitted using MEX n predictors achieving the highest D^2 ($n = 37$).

A subset of the strongest maximum temperature, minimum temperature and moisture index interactions extracted from the best performing MEX n are illustrated in Figure 4.5. Predicted probabilities for *Eucalyptus globoides* presence were associated with hot regions of Victoria but with less severe extremes as indicated by MAXT- V_5 . Conversely, *Eucalyptus radiata* was associated with cooler regions but with more severe maximum and minimum temperature extremes best represented at 30-year return intervals. Both *Olearia argophylla* and *Bedfordia arborescens* were associated with wetter summers suggesting a low tolerance to seasonal moisture stress.

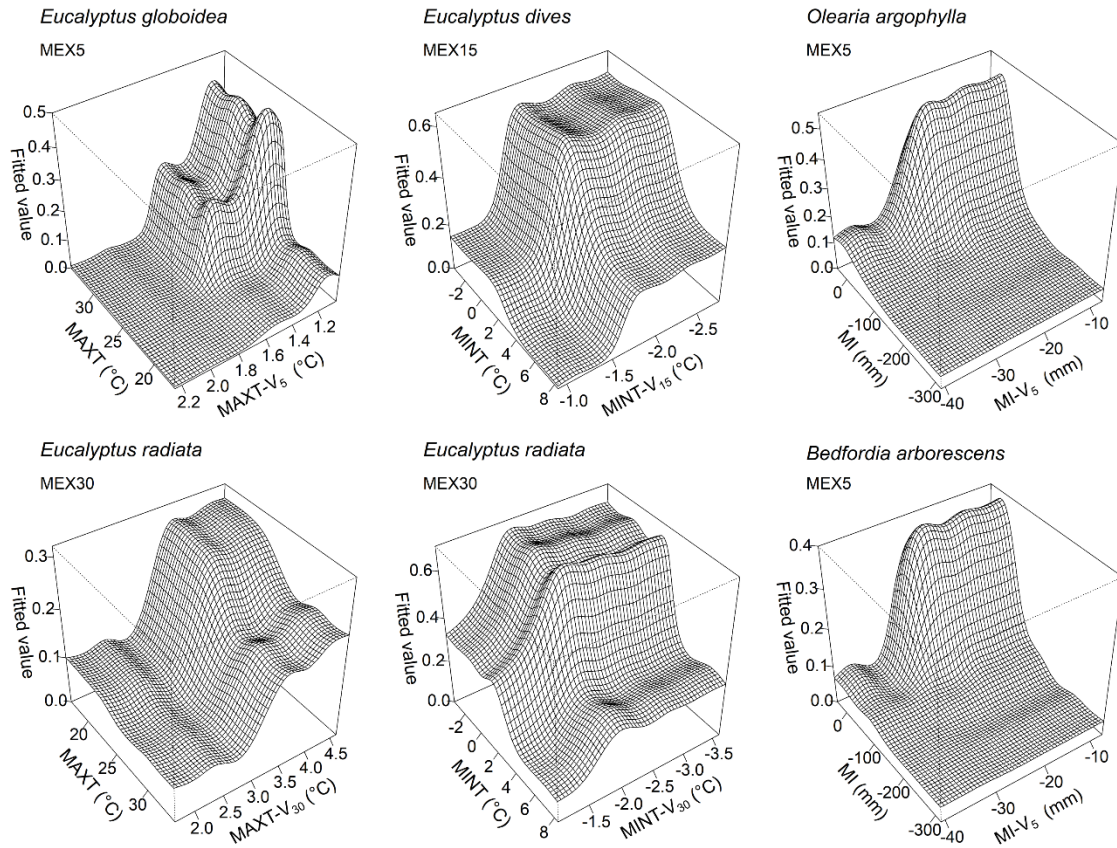


Figure 4.5: Smoothed perspective plots of the interaction between mean annual maximum temperature (MAXT), minimum temperature (MINT) and moisture index (MI) extremes, and the asymmetric variability in extremes (V_n ; where n = expected return interval in years).

The spatial distributions of *Cassinia longifolia* when predicted using the MEX, MEX σ , MEX5 and MEX40 variable sets are illustrated in Figure 4.6. Cross-validated model performance was best when using a 40-year extreme return interval (MEX40; AUC = 0.91, D^2 = 0.38), resulting in a considerably different spatial distribution and improved performance metrics relative to MEX (AUC = 0.82, D^2 = 0.19). The MEX5 and MEX40 models tended to predict higher probabilities that were accompanied by an improvement in discrimination ability (i.e. AUC). The MEX5 and MEX40 models predict large differences in spatial connectivity and existence of suitable climate throughout the alpine regions in eastern Victoria, despite being drawn from the same distribution of extremes.

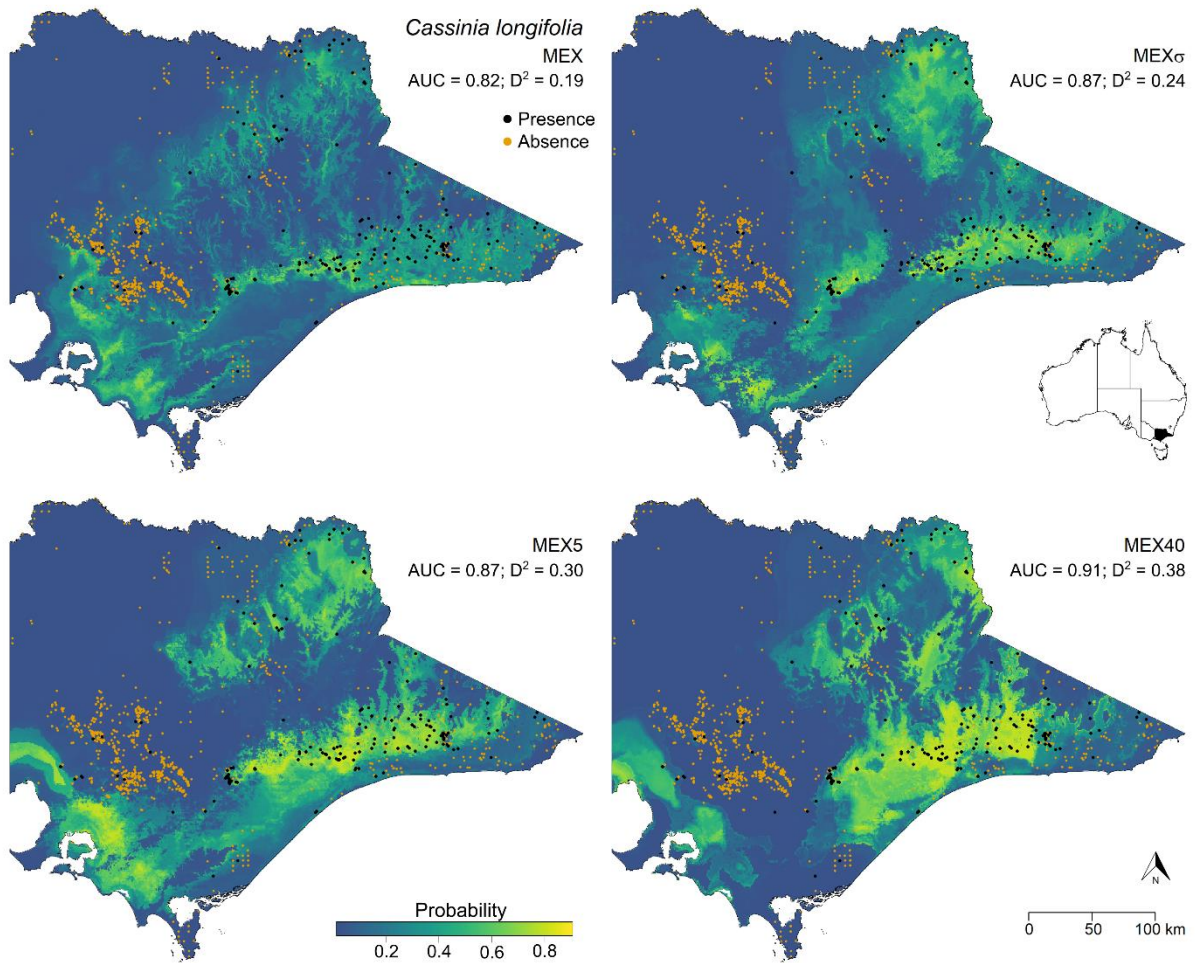


Figure 4.6: Predicted species distribution model probabilities for *Cassinia longifolia* fitted to climate extremes (MEX), climate extremes with symmetric variability (MEX σ) and climate extremes with asymmetric variability (MEX n) corresponding to expected return intervals of n years.

The MEX n models typically demonstrated spatial and statistical trends in the expansion and contraction in the predicted probability of presence with perturbations in the expected extreme return intervals. Examples are illustrated for *Acacia melanoxylon* and *Eucalyptus radiata* for return intervals of 5, 15 and 30 years across two subset regions in Figure 4.7. Directional trends in D^2 and gradual shifts in the expansion and contraction of predicted probabilities were common features of the MEX n family of models. These trends and shifts were illustrated in a series of animations for each species and sequential expected return interval across Victoria as part of the digital appendices (Appendix 4.H).

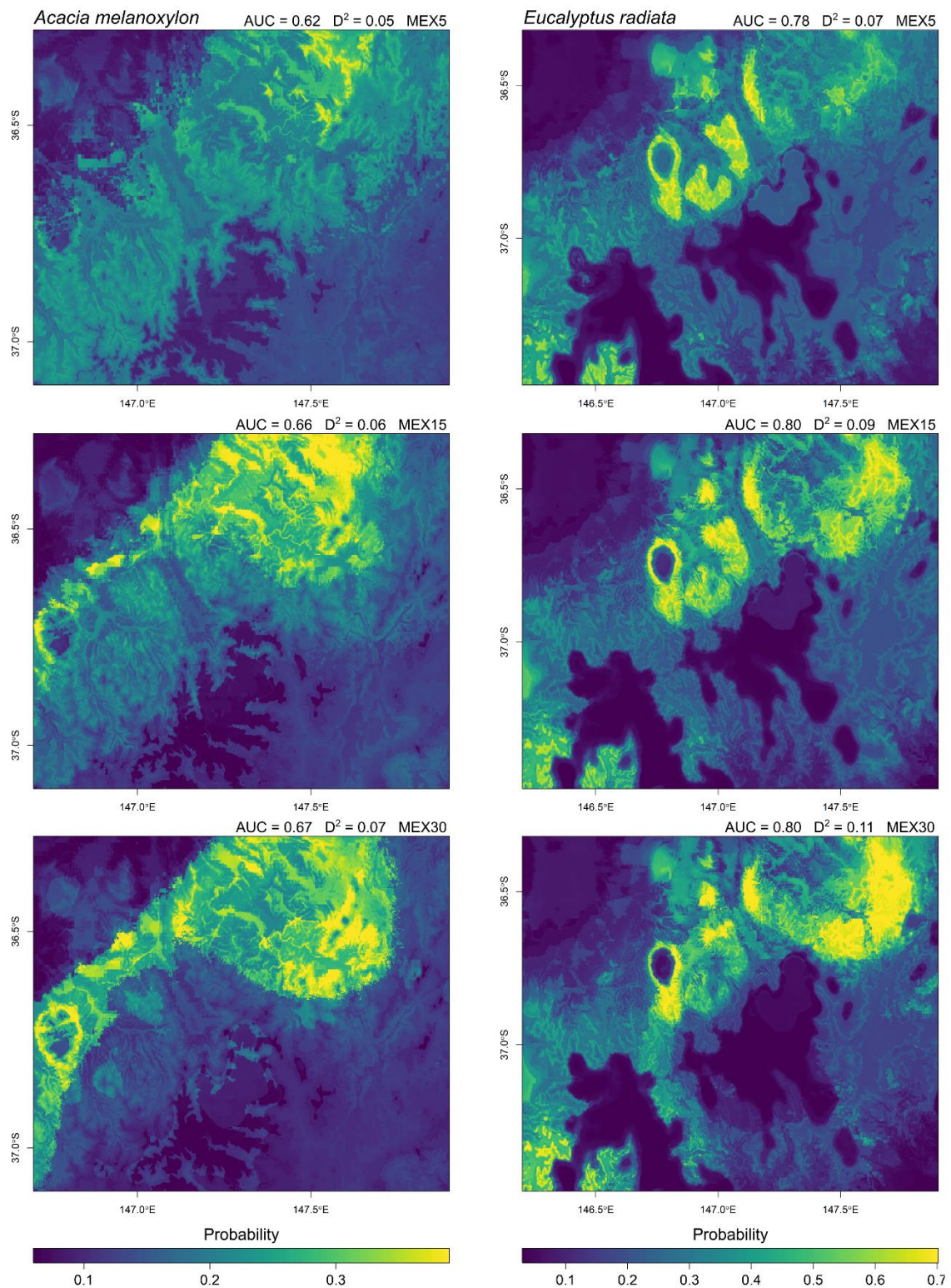


Figure 4.7: Predicted distribution of *Acacia melanoxylon* and *Eucalyptus radiata* fitted using climate extremes with asymmetric variability corresponding to expected return intervals of 5, 15 and 30 years.

4.4. DISCUSSION

Our analyses demonstrate how using extreme value theory to quantify the temporal dynamics of interannual extremes at multi-decadal timescales can improve species distribution models. Unlike extreme indices more commonly used in ecological studies, our probabilistic approach relies upon extreme value theory and therefore is suited to represent the rarest, most severe events (Wang et al. 2013). Extreme indices are undoubtedly effective for ecological modelling; however, they typically depend on specific thresholds that assume a level of impact that is appropriate for the response of interest. Percentiles are also limited as they are sensitive to the temporal range of the historical climate series used in the calculation and will be biased towards particular time periods within this range (unless for example the data series is first segmented into meaningful sets, such as annual values, in which case EVT could also be applied).

The characterisation of ecologically meaningful thresholds and extreme climate events remains a challenge (Smith 2011; Suggit et al. 2017) given the potential for interactions between climatic factors (see Mitchell et al. 2014), variability in spatial and temporal scales of influence, and the complex interdependencies that shape ecological systems. Extreme variables derived from the GEV distribution adapt to the type and available time series of data, allow for the frequency and magnitude of extremes to be evaluated simultaneously, and provide flexibility in how extremes are represented. The ability to easily modify the expected return intervals to represent the rarest extremes may be particularly advantageous for meta-analyses given the diversity of intra (e.g. growth stages, genomics, phenotypic variation) and inter-species responses to environmental conditions. By incorporating the tail centre (i.e. the location parameter of the GEV distribution) and measures of variability that reflect the skewed distribution of extremes, these variables can also be readily linked to projected climate change scenarios where both the mean, variability and shape of the underlying distribution may change. Furthermore, when ecological knowledge allows for the identification of thresholds with important impacts, the GEV distribution can be used to determine where these conditions are most likely to occur, in addition to how frequently they can be expected.

Our methods and findings improve upon those of Zimmerman et al. (2009), with two important differences. Firstly, we used both spatially blocked and randomly sampled cross-

validation designs to evaluate our results in the context of both extrapolation and interpolation error, a distinction that is of critical importance given that the environmental niche will shift in both space and time with changes in climate regimes. Secondly, we extracted the frequency and magnitude of adverse climatic conditions (i.e. hotter, colder or drier extremes) directly from the asymmetrical GEV distribution, in addition to testing the efficacy of a single symmetrical measure of variability. A near-universal improvement in model performance was found when using any measure of variability with typical seasonal extremes and a randomly sampled set of points for cross-validation. This result was consistent with Zimmerman et al. (2009); however, when cross-validating using spatial blocks to provide a better estimate of extrapolation error, we found that only the asymmetric, directionally dependent component of variability provided a significant overall performance improvement. A simple but probable explanation for this finding is that the skewed distribution of interannual extreme series better captures the true constraints on the realised climatic niche. Our approach isolates the expected frequency and magnitude of the coldest winters, and the hottest and driest summers rather than relying on an isotropic measure of variability.

We found that varying return intervals lead to similar spatial patterns and model predictions tended to expand and contract around the leading and trailing edges of the species distribution. This was consistent with previous work by Zimmerman et al. (2009) in their analysis of tree species responses to variability in climate extremes. This behaviour can be observed for most species modelled and reflects potential source-sink dynamics at the edges of the realised climatic niche (Zimmerman et al. 2009). Furthermore, there were often very large differences in mapped distributions when modelled with or without corresponding measures of extreme variability, despite only relatively small differences in statistical performance. In some cases, the breadth of this expansion and contraction suggested extreme variability may also reflect the opening and closing of climate corridors (e.g. Early & Sax 2011) throughout the time series, allowing for the establishment of sink populations. For example, mutually exclusive differences in the spatial connectivity of modelled probabilities for *Cassinia longifolia* at return intervals of 5 and 40 years (southwest versus the alpine regions of the distribution) are coupled with small numbers of presences in these locations.

One of the key barriers to applying the methods we have described is the availability of climate datasets with enough spatial and temporal extent and resolution to be ecologically meaningful. While there are potential approaches to fusing long term averages of fine-grained

data with high frequency time series of spatially coarse data (e.g. Kriticos et al. 2012), error in climate surfaces will likely be high relative to locally calibrated surfaces for many parts of the world (e.g. Stewart & Nitschke 2017/Chapter 2; Stewart et al. 2017/Chapter 3). Fortunately, methods and tools such as ANUSPLIN (Hutchinson & Xu 2013) are readily available for developing locally calibrated climate surfaces at user-defined spatial and temporal resolutions provided suitable weather station observations are available. The datasets we used were specifically designed for ecological modelling in the study region but are limited to 24 and 33 years of data for the moisture index and temperature, respectively. EVT can produce reliable return intervals with relatively short time series (Gaines & Denny 1993), but more careful consideration concerning the length of the data series is required particularly where absolute values (e.g. for species-specific thresholds) are important (Wang et al. 2013). Future research may benefit from fitting the GEV distributions to longer time series of historical data to improve the representation of extreme magnitudes and frequencies.

4.5. CONCLUSION

Understanding the behaviour of extremes and their influence on the function of extant ecosystems is fundamental to anticipating the potential implications of a changing climate. The results of this study demonstrate that extreme climate variables, derived from EVT and reflecting interannual dynamics, improve correlative distribution models for plant species. The variables presented provide an additional set of tools for ecological modellers that are likely to be useful for climate change studies in that they capture the mean, spread and shape of extreme distributions. Although the improvements in model performance when including interannual variability of extremes are often only small, they can lead to large differences in the spatial configuration of predicted species distributions. The difference in these spatial configurations frequently correspond to the leading and trailing edges of species distributions, indicating that summarised measures of interannual variability can capture climate-driven source-sink dynamics at the edge of the species range. Identifying those regions that support resistance or resilience to climate extremes can also assist in guiding important decision-making processes for conservation and forest management. Further exploration of extreme value theory may provide additional opportunities to develop effective spatial predictors for correlative ecological analyses, particularly with respect to temporal variability which has not been thoroughly explored.

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4.7. APPENDICES

APPENDIX 4.A: SURVEY DATA COLLATED FROM FIELD CAMPAIGNS ACROSS VICTORIA

All records were aggregated to the species level as part of the data cleaning procedure, as sub-species were not indicated in many entries. Only one species (*Acacia verticillata*) used in the modelling study included more than one subspecies (*Acacia verticillata subsp. verticillata* and *Acacia verticillata subsp. ovoides*).

Table 4.A.1: Details of floristic survey data collated from field campaigns conducted across Victoria.

Survey dataset	Survey years	Site dimensions	No. sites included	No. unique species
Victorian forest monitoring program ^a	2009–2015	50 m ² (nested) – 400 m ² circular plots	512	1,613
Leadbeater’s Possum targeted surveys	2015–2016	10,000 m ² quadrats	287	61
VicForests	2016–2017	3 x 50 m ² – 1,250 m ² circular plots	68	124
Forest ecology research network (Central Highlands) ^b	2012–2014	400 m ² – 900 m ² quadrats	162	58
Forest ecology research network (Otways Heathland) ^c	2013–2014	9 m ² quadrats at ridge (x2), mid-slope (x2), and gully positions (x2)	74	87
Faunal refuges project ^d	2010–2011	2 m ² (nested) – 64 m ² quadrats	192	239
Gippsland retrospective and Hawkeye ^d	2010–2012	7 x 1 m ² quadrats along 3 radial 50 m transects	152	512
Pre and post fire flora monitoring surveys ^d	2006–2013	400 m ² quadrats	212	875
Otways Hawkeye and University of Melbourne ^d	2010–2012	33 x 2 m ² quadrats along 100 m transect (random bearing)	205	415
Total number across all surveys			1,864	1,941

^a Haywood et al. 2018; ^b Kasel et al. 2017, Fairman et al. 2017, Fedrigo et al. 2019; ^c Chick et al. 2018; ^d Leonard et al. 2016, Haslem et al. 2016.

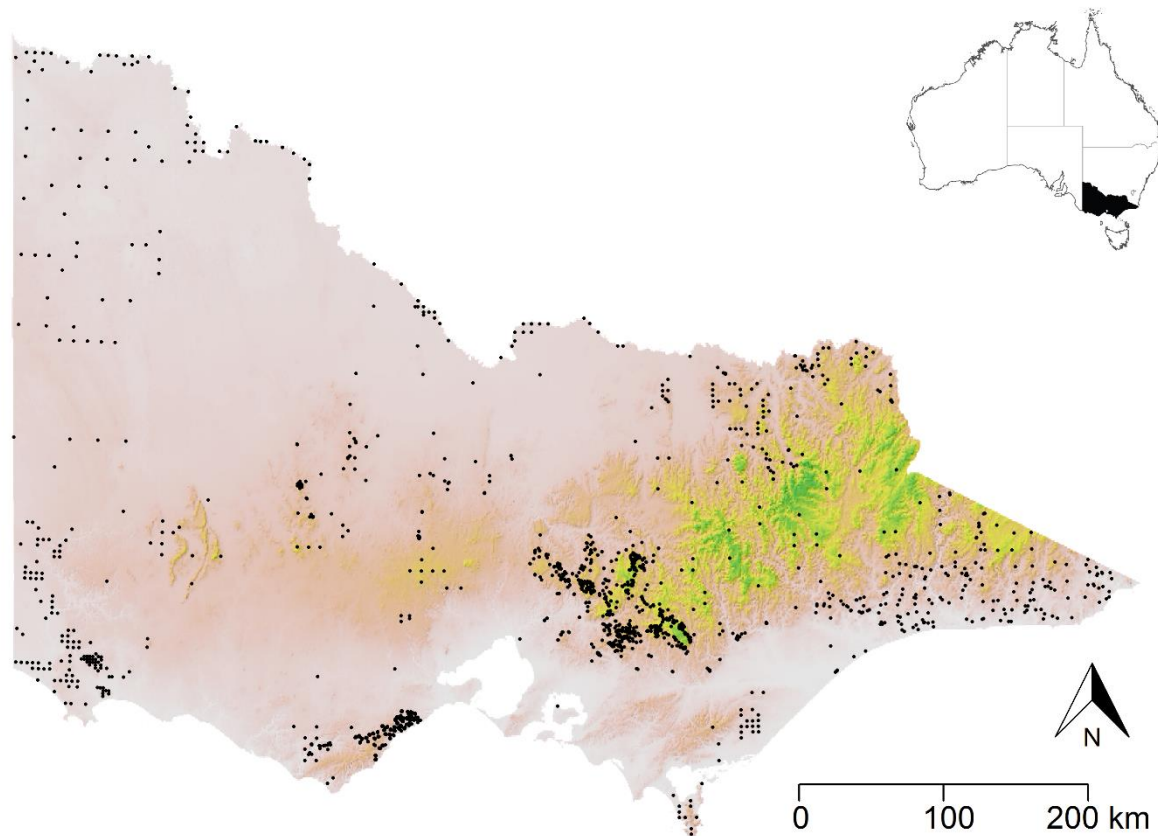


Figure 4.A.1: Locations of floristic survey ($n = 1,864$) data collated from field campaigns conducted in forested sites across Victoria.

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APPENDIX 4.B: INTERPOLATION, CALCULATION AND CROSS-VALIDATION OF CLIMATE DATASETS

Daily vapour pressure and precipitation datasets were interpolated using weather station observations collected by the Australian Bureau of Meteorology (obtained via the SILO patched point dataset; Jeffrey et al. 2001) and the GEODATA 9 Second Digital Elevation Model (Fenner School of Environment and Society and Geoscience Australia 2008). All interpolations were performed using ANUSPLIN 4.4 (Hutchinson & Xu 2013). Several interpolation methods were evaluated for each variable to maximise the quality of each set of daily surfaces. These methods broadly included both direct interpolation methods (using observations for each day in isolation), and anomaly or indicator-based methods (where daily interpolations are supported by secondary surfaces).

Gridded daily vapour pressure surfaces were interpolated to enable to calculation of vapour pressure deficit, which is a component of reference evapotranspiration calculations. Two approaches were evaluated; a direct interpolation approach and an anomaly-based approach (Table 4.B.1). Under the direct approach, the square root of the vapour pressure (McKenney et al. 2004) was interpolated using ordinary trivariate splines (full spline dependence upon latitude, longitude and elevation), and transformed back into units of hPa separately for each day. The anomaly approach requires climate normals to first be computed. Climate normals at each weather station for the 1981–2010 reference period were first corrected for any biases induced by record length using adjustments based on regression on neighbouring stations (Hopkinson et al. 2012; Stewart & Nitschke 2017/Chapter 2). The square root of monthly mean vapour pressure climate normals was then interpolated using ordinary trivariate splines and was subsequently transformed back to units of hPa. Daily anomalies were then computed by subtracting climate normals of the appropriate month from daily observations. Anomalies were then interpolated using bivariate splines (full spline dependence upon latitude and longitude only), and final daily predictions were obtained by adding the climate normals to the interpolated anomalies. A leave-one-out cross-validation approach was applied to evaluate model performance. Note that daily anomalies were cross-validated with predicted as opposed to actual climate normal points to ensure a fair comparison with the daily direct approach. Overall, the daily anomaly method performed better than the daily direct approach,

despite a slightly higher mean absolute error. The daily anomaly vapour pressure dataset was interpolated and used throughout the remaining analysis.

Table 4.B.1: Spatially and temporally pooled cross-validation error statistics for monthly mean and daily vapour pressure interpolated using direct and anomaly-based approaches.

Vapour Pressure (hPa)	r^2	MAE	RMSE	RSR	BIAS
Monthly Mean (1981–2010)	0.97	0.29	0.38	0.17	0.00
Daily Anomaly (1981–2014)	0.87	0.81	1.20	0.36	-0.01
Daily Direct (1981–2014)	0.86	0.78	1.24	0.37	-0.03

r^2 = coefficient of determination, MAE = mean absolute error, RMSE = root mean square error, RSR = ratio of the RMSE to the standard deviation of the observations, BIAS = mean error.

Gridded daily and monthly precipitation surfaces were interpolated to calculate the moisture index. Several approaches were evaluated for each temporal frequency (Table 4.B.2). With the exception of anomaly surfaces, all precipitation interpolations used a smoothed DEM (Gaussian filter with a standard deviation of 10 and a search radius of 0.0825° , optimised using cross-validation) to account for the lack of strong correlation with elevation at scales between 5 and 10 km and improve interpolation performance (Hutchinson 1998; Sharples et al. 2005; Stewart et al. 2017/Chapter 3). The square root of monthly mean (corrected using regression on neighbouring stations, as with vapour pressure), monthly direct, and daily direct precipitation were interpolated using ordinary trivariate splines, and subsequently transformed back to units of mm. Monthly precipitation anomalies were calculated by first subtracting the appropriate monthly mean surface, interpolating the residuals using a bivariate spline, and then adding the results back to the climate normals. The monthly direct method performed best across all metrics except for mean error and was used for the remainder of the analysis. Daily anomalies were computed as a fraction of the monthly precipitation (direct), interpolated using a bivariate spline, and the values were calculated by multiplying the fractional anomaly by the monthly total. An indicator approach was also attempted (Hutchinson et al. 2009), where positive precipitation (> 0 mm) records were interpolated and filtered using binary predictions of precipitation presence or absence (0/1 interpolated using bivariate spline). Overall, the daily anomaly method was selected on the basis of interpolation performance relative to the daily direct method, and the absence of spatial anomalies which were present in the daily indicator surfaces.

Table 4.B.2: Spatially and temporally pooled cross-validation error statistics for monthly mean, monthly and daily precipitation interpolated using direct, anomaly and indicator-based approaches.

Precipitation (mm)	r^2	MAE	RMSE	RSR	BIAS
Monthly Mean (1981–2010) ^a	0.92	4.65	7.65	0.28	-0.19
Monthly Direct (1981–2014) ^b	0.91	7.77	13.12	0.30	-0.53
Monthly Anomaly (1981–2014) ^c	0.90	8.26	13.98	0.32	0.10
Daily Direct (1981–2014)	0.83	0.66	2.20	0.42	-0.09
Daily Anomaly (1981–2014)	0.84	0.66	2.10	0.40	-0.01
Daily Indicator (1981–2014)	0.83	0.61	2.21	0.42	-0.11

r^2 = coefficient of determination, MAE = mean absolute error, RMSE = root mean square error, RSR = ratio of the RMSE to the standard deviation of the observations, BIAS = mean error.

^a MAE = 8.5%, RMSE = 14.0% and BIAS = 0.0% when expressed as a proportion of the mean.

^b MAE = 14.6%, RMSE = 24.7% and BIAS = 0.0% when expressed as a proportion of the mean.

^c MAE = 15.6%, RMSE = 26.3% and BIAS = 0.0% when expressed as a proportion of the mean.

Potential outliers were identified and removed using the bad data flag option in ANUSPLIN (where residual is greater than 3.6 standard deviations of the interpolation variance). All outliers were included during cross-validation to ensure conservative error estimates but were not used for generating the final surfaces.

Daily reference evapotranspiration (FAO-56) was generated at a spatial resolution of approximately 250 m using a range of input data following Allen (1998):

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

where ET_0 is the reference evapotranspiration (mm day^{-1}), R_n is the net incoming solar radiation ($\text{MJ m}^{-2}\text{d}^{-1}$), G is the soil heat flux density ($\text{MJ m}^{-2}\text{d}^{-1}$), T is the mean daily temperature ($^{\circ}\text{C}$), u_2 is the wind speed at 2m height (m s^{-1}), e_s is the saturation vapour pressure (kPa), e_a is the vapour pressure, Δ is the slope of the vapour pressure curve ($\text{kPa } ^{\circ}\text{C}^{-1}$) and γ is the psychrometric constant ($\text{kPa } ^{\circ}\text{C}^{-1}$).

Daily saturation vapour pressure was calculated with temperature data using a recalibration of the August-Roche-Magnus equation (Alduchov & Eskridge 1996);

$$e_s(T) = 6.1094 \times \exp^{\frac{17.625 \times T}{243.04 + T}}$$

where T is the mean daily temperature.

Gridded daily solar radiation data (available from January 1990 to present at approx. 5 km cell resolution) produced using hourly satellite images as part of the AWAP project (Raupach et al. 2009; Raupach et al. 2012) were obtained from the Australian Bureau of Meteorology (<http://www.bom.gov.au/>). Imagery from the Geostationary Meteorological Satellite series operated by Japan Meteorological Agency (JMA) and from GOES-9 operated by the National Oceanographic & Atmospheric Administration (NOAA) for the JMA is used by the BoM to process each daily scene. The data series provided by the BoM is reported as being accurate to $\pm 3 \text{ MJ m}^{-2} \text{ d}^{-1}$ and has the advantage of correcting for the influence of cloud cover on solar exposure. Analysis of the data series between January 1990 and July 2014 indicated that 4.8% of the scenes were not available (due to data quality issues, technical interruptions, etc.). In order to ensure a continuous data series, gaps for any given day were filled by taking the long-term average across all scenes within 5 days of the target date.

Daily wind speed surfaces (calibrated at 2 m height; approx. 1 km cell resolution) were downloaded from the Commonwealth Scientific and Industrial Research Organisation (CSIRO; McVicar 2011) data access portal (<https://data.csiro.au>). While the effect of topographic complexity on wind speed (see Sharples *et al.* 2010) is not incorporated into this dataset, it is spatially continuous, temporally complete between January 1975 and December 2015, and typically shows a decrease in wind speed with distance from the coast. The minimum wind speed was set to 0.5 m s^{-1} to minimise underestimation of reference evapotranspiration that may occur under still conditions (Allen 1998).

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APPENDIX 4.C: SELECTION OF CLIMATE VARIABLES

The exclusion of many variables was required to enable a systematic approach to evaluating climate extremes as predictors of species distributions. It was also critical to keeping the number of predictors low enough relative to the number of observations available. Many climate variables were initially considered and evaluated for inclusion as model predictors. Commonly used bioclimatic variables were typically excluded due to high correlations with seasonal extremes and to prevent confounding effects on extremes. For example, mean annual temperatures and isothermality were highly correlated with seasonal maximum and minimum temperature extremes. The temperature extremes are however both analogous to BIO5 (maximum temperature of the warmest month) and BIO6 (minimum temperature of the coldest month), while providing a strong statistical basis for the distribution of extremes via the asymmetric Generalised Extreme Value (GEV) distribution.

The moisture index reflects a combination of temperature and precipitation based bioclimatic variables (e.g. BIO8 through BIO19). It was favoured over precipitation-based metrics as it represents water availability in a single measure. One of the key advantages of using the moisture index was that unlike precipitation-based metrics and ratio-based aridity indices, the tail centre of the data was not strongly correlated (i.e. $r < 0.7$) with interannual variability. Maximum temperature and vapour pressure deficit extremes were strongly correlated with one another ($r > 0.8$; despite linear versus non-linear scaling with elevation). Maximum temperature was ultimately selected as it was less strongly correlated with the moisture index and was the only remaining variable to show clear correlations with elevation at very fine spatial scales (non-linear effects and smoothing evident for the minimum temperature and moisture index).

Several extreme indices were assessed and subsequently excluded for a variety of reasons. Many of the precipitation metrics demonstrated near-identical spatial distributions and also demonstrated collinearity with interannual variability. For example, mean precipitation intensity was strongly correlated with the variability of precipitation intensity. Furthermore, the majority of precipitation-based metrics shared very similar distributions with the moisture index, and the maximum number of consecutive wet or dry days and their interannual variability showed very strong, patchy spatial artefacts. For maximum temperature, counts of

summer days ($> 25\text{ }^{\circ}\text{C}$) were very strongly correlated with typical annual extremes, icing days ($< 0\text{ }^{\circ}\text{C}$) were absent except for very small areas of the state, and hot spells (where there are 6 or more consecutive days above the 90th percentile) were almost entirely uniform across the state. For minimum temperature, counts of frost days ($< 0\text{ }^{\circ}\text{C}$) were strongly correlated with the tail centre of extremes, tropical nights ($> 25\text{ }^{\circ}\text{C}$) were uncommon and spatially uniform at the majority of survey sites, and cold spells (where there are at least 6 consecutive days below the 10th percentile) were almost entirely uniform across the state. Variables based on total and consecutive counts may be useful for modelling the distribution of species; however, they are likely to be more useful when adjusted to more applicable biological thresholds. As 37 species were selected it was not feasible to calibrate surfaces for individual species, especially considering the volume of data to be processed (e.g. temperature variables have $2,072 \times 3,607 \times 12,225$ pixels in each daily dataset).

The variable selection and elimination process left few options for evaluating the influence of extremes after evaluating the available data. This led to the selection of maximum temperature, minimum temperature and the moisture index for representing climate extremes. Spatial predictors not related directly to climate extremes were excluded to avoid confounding model comparisons. This approach was taken to aid in the explanation of our conceptual approach, interpretation of model results (e.g. interaction plots and mapping) and to minimise the number of input variables and parameter sets used throughout the analysis.

APPENDIX 4.D: EXAMPLE OF CLIMATE VARIABLES USED FOR SPECIES DISTRIBUTION

MODELLING

Annual tails = Maximum (maximum temperature) or minimum (minimum temperature and moisture index) of monthly means
 Tail centre = Location parameter of the Generalised Extreme Value (GEV) distribution fit to annual tails
 Tail edge = 1 in 50 year return interval of climate extremes derived from fitted GEV distribution

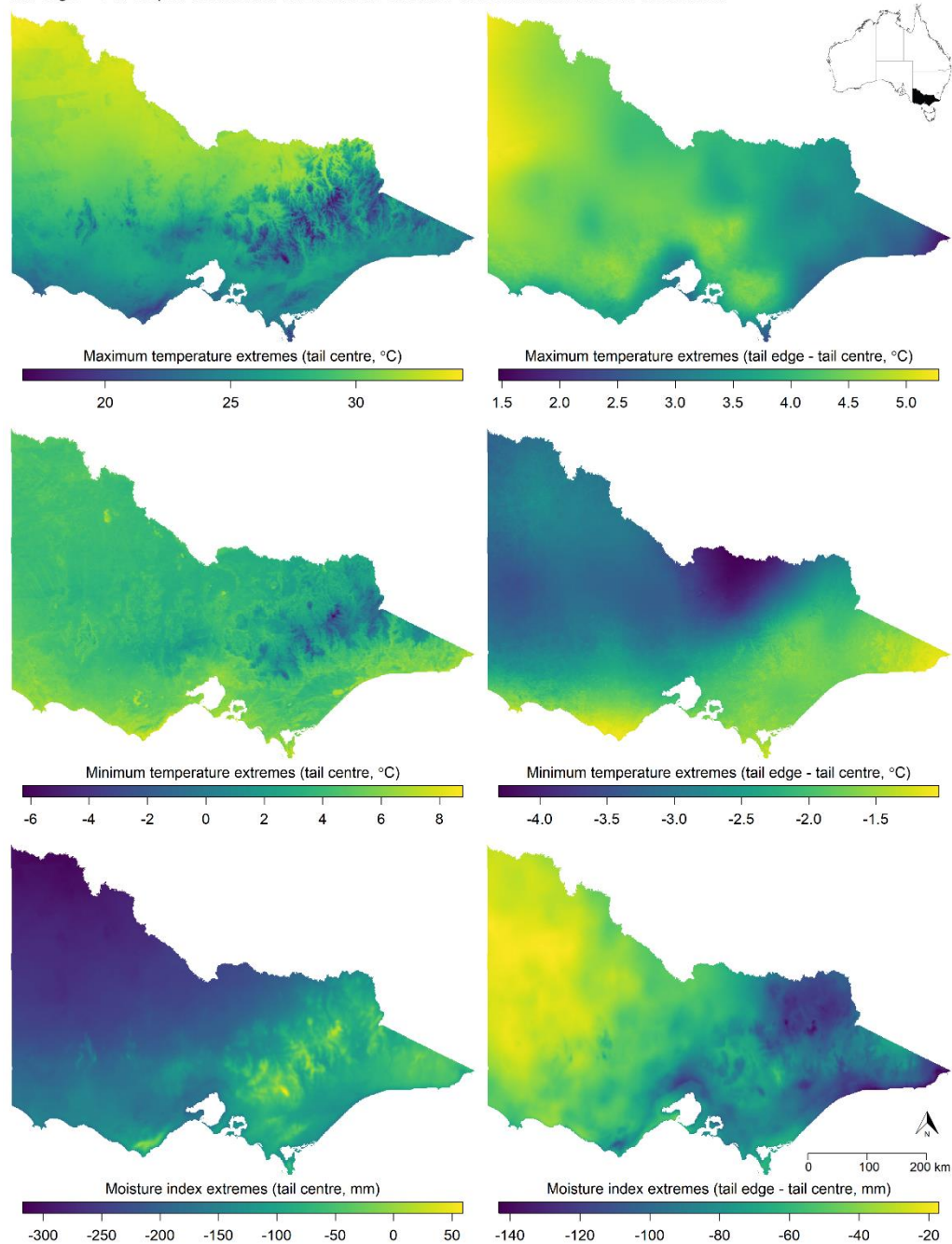


Figure 4.D.1: Spatial distribution of maximum temperature, minimum temperature and moisture index extremes (tail centre) and a representation of the variability of these extremes (tail edge – tail centre) at a 50-year return interval across Victoria, southeast Australia.

APPENDIX 4.E: CROSS-VALIDATION PERFORMANCE FOR SPECIES DISTRIBUTION

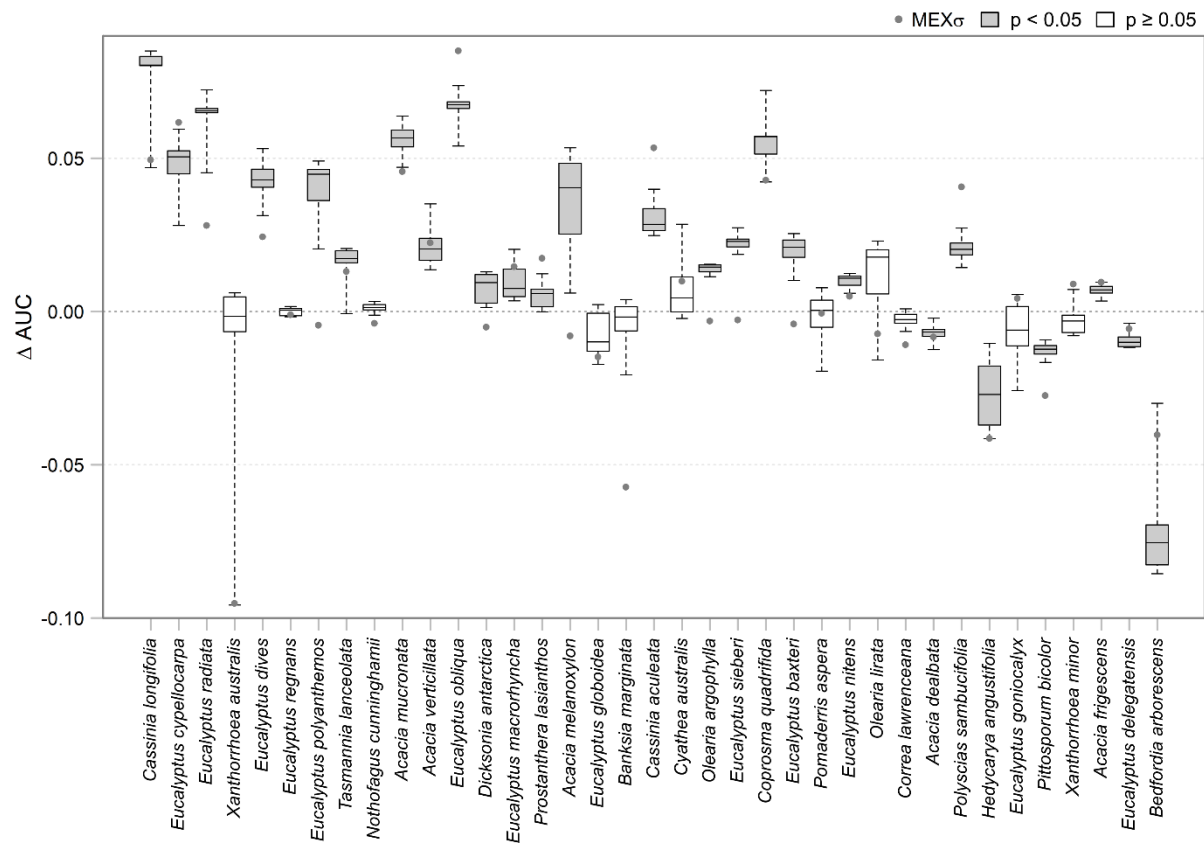
MODELS FITTED USING MEX_n AND MEX_σ RELATIVE TO MEX PREDICTORS

Figure 4.E.1: Cross-validated change in the area under the receiver operating characteristic (AUC) for SDMs fitted with extremes and alternate corresponding measures of variability for 37 species. Results are expressed relative to typical monthly extremes (MEX). Boxplots (box corresponds to interquartile range, whiskers to data extremes) show results for models using asymmetric measures of variability derived from extremes of increased magnitude and decreased frequency corresponding to return intervals of between 5 and 50 years. Points correspond to models using symmetric measures of variability (scale parameter of the GEV distribution).

APPENDIX 4.F: CROSS-VALIDATION PERFORMANCE FOR SPECIES DISTRIBUTION MODELS FIT USING MEX, MEX_n AND MEX σ

Table 4.F.1: Cross-validated (spatially blocked k-fold) species distribution model performance metrics for 37 species fit using boosted regression trees with extremes and variability of maximum temperature, minimum temperature and a moisture index as spatial predictors in Victoria, southeast Australia. Extremes derived from Generalised Extreme Value (GEV) distributions. Results for all MEX_n variants are provided in the spreadsheet titled 'sdm_extremes_results_complete.xlsx'.

Species	P	A	K	M	<u>MEX</u>		<u>MEXσ</u>		<u>MEX_n</u>	
					AUC	D ²	AUC	D ²	AUC	D ²
<i>Acacia dealbata</i>	490	1316	6	MEX15	0.802	0.190	0.794	0.179	0.800	0.199
<i>Acacia frigescens</i>	136	1670	5	MEX	0.876	0.256	0.885	0.213	—	—
<i>Acacia melanoxylon</i>	297	1509	6	MEX30	0.615	0.036	0.607	0.036	0.668	0.072
<i>Acacia mucronata</i>	137	1669	5	MEX5	0.767	0.137	0.813	0.131	0.831	0.224
<i>Acacia verticillata</i>	176	1630	5	MEX30	0.766	0.121	0.789	0.120	0.790	0.175
<i>Banksia marginata</i>	210	1596	5	MEX30	0.885	0.256	0.827	0.222	0.887	0.295
<i>Bedfordia arborescens</i>	183	1623	6	MEX5	0.790	0.102	0.750	0.063	0.760	0.136
<i>Cassinia aculeata</i>	271	1535	6	MEX σ	0.740	0.138	0.794	0.182	—	—
<i>Cassinia longifolia</i>	177	1629	6	MEX40	0.824	0.195	0.874	0.242	0.909	0.379
<i>Coprosma quadrifida</i>	445	1361	6	MEX5	0.702	0.078	0.745	0.113	0.774	0.152
<i>Correa lawrenceana</i>	172	1634	4	MEX35	0.871	0.196	0.860	0.181	0.867	0.202
<i>Cyathea australis</i>	222	1584	5	MEX5	0.774	0.088	0.784	0.079	0.802	0.121
<i>Dicksonia antarctica</i>	406	1400	5	MEX45	0.842	0.314	0.836	0.252	0.854	0.357
<i>Eucalyptus baxteri</i>	156	1650	5	MEX10	0.803	0.105	0.799	0.090	0.817	0.123
<i>Eucalyptus cypellocarpa</i>	276	1530	6	MEX25	0.724	0.076	0.786	0.160	0.783	0.180

Species	P	A	K	M	<u>MEX</u>		<u>MEXσ</u>		<u>MEXn</u>	
					AUC	D^2	AUC	D^2	AUC	D^2
<i>Eucalyptus delegatensis</i>	101	1705	4	MEX	0.950	0.425	0.944	0.342	–	–
<i>Eucalyptus dives</i>	164	1642	5	MEX15	0.809	0.194	0.834	0.222	0.862	0.274
<i>Eucalyptus globoidea</i>	134	1672	5	MEX5	0.937	0.295	0.922	0.263	0.939	0.359
<i>Eucalyptus goniacalyx</i>	98	1708	5	MEX5	0.911	0.308	0.916	0.289	0.916	0.344
<i>Eucalyptus macrorhyncha</i>	201	1605	5	MEX10	0.890	0.318	0.905	0.374	0.910	0.393
<i>Eucalyptus nitens</i>	84	1722	4	MEX35	0.899	0.279	0.904	0.285	0.912	0.292
<i>Eucalyptus obliqua</i>	459	1347	5	MEX σ	0.708	0.107	0.793	0.190	–	–
<i>Eucalyptus polyanthemos</i>	153	1653	5	MEX20	0.853	0.183	0.848	0.150	0.894	0.249
<i>Eucalyptus radiata</i>	187	1619	5	MEX30	0.731	0.022	0.759	0.045	0.802	0.109
<i>Eucalyptus regnans</i>	372	1434	4	MEX10	0.920	0.389	0.919	0.385	0.921	0.451
<i>Eucalyptus sieberi</i>	147	1659	5	MEX10	0.884	0.267	0.882	0.251	0.905	0.300
<i>Hedycarya angustifolia</i>	136	1670	5	MEX5	0.798	0.058	0.757	0.045	0.779	0.060
<i>Nothofagus cunninghamii</i>	166	1640	4	MEX25	0.953	0.356	0.949	0.367	0.956	0.409
<i>Olearia argophylla</i>	309	1497	5	MEX5	0.806	0.106	0.803	0.133	0.821	0.149
<i>Olearia lirata</i>	215	1591	6	MEX5	0.695	0.063	0.687	0.067	0.679	0.098
<i>Pittosporum bicolor</i>	110	1696	4	MEX	0.849	0.171	0.821	0.100	–	–
<i>Polyscias sambucifolia</i>	273	1533	5	MEX σ	0.797	0.181	0.838	0.206	0.838	–
<i>Pomaderris aspera</i>	333	1473	6	MEX5	0.809	0.199	0.809	0.178	0.811	0.232
<i>Prostanthera lasianthos</i>	118	1688	4	MEX σ	0.765	0.110	0.782	0.159	–	–
<i>Tasmania lanceolata</i>	121	1685	4	MEX30	0.868	0.128	0.881	0.154	0.889	0.191
<i>Xanthorrhoea australis</i>	126	1680	4	MEX35	0.862	0.108	0.767	0.054	0.868	0.198

Species	P	A	K	M	<u>MEX</u>		<u>MEXσ</u>		<u>MEXn</u>	
					AUC	D^2	AUC	D^2	AUC	D^2
<i>Xanthorrhoea minor</i>	152	1654	5	MEX5	0.847	0.188	0.856	0.192	0.855	0.202

P = presence; A = absence; k = number of block cross-validation folds; M = model achieving the highest D^2 , AUC = area under the receiver operating characteristic; D^2 = proportion of deviance explained; MEX = extremes only (location parameter of GEV distribution); MEX σ = extremes and non-directional variability (scale parameter of GEV distribution); MEX n = extremes and directionally-dependent variability (expected return interval of n years minus the location parameter).

APPENDIX 4.G: SPECIES RESPONSES TO EXTREME CLIMATE VARIABLES

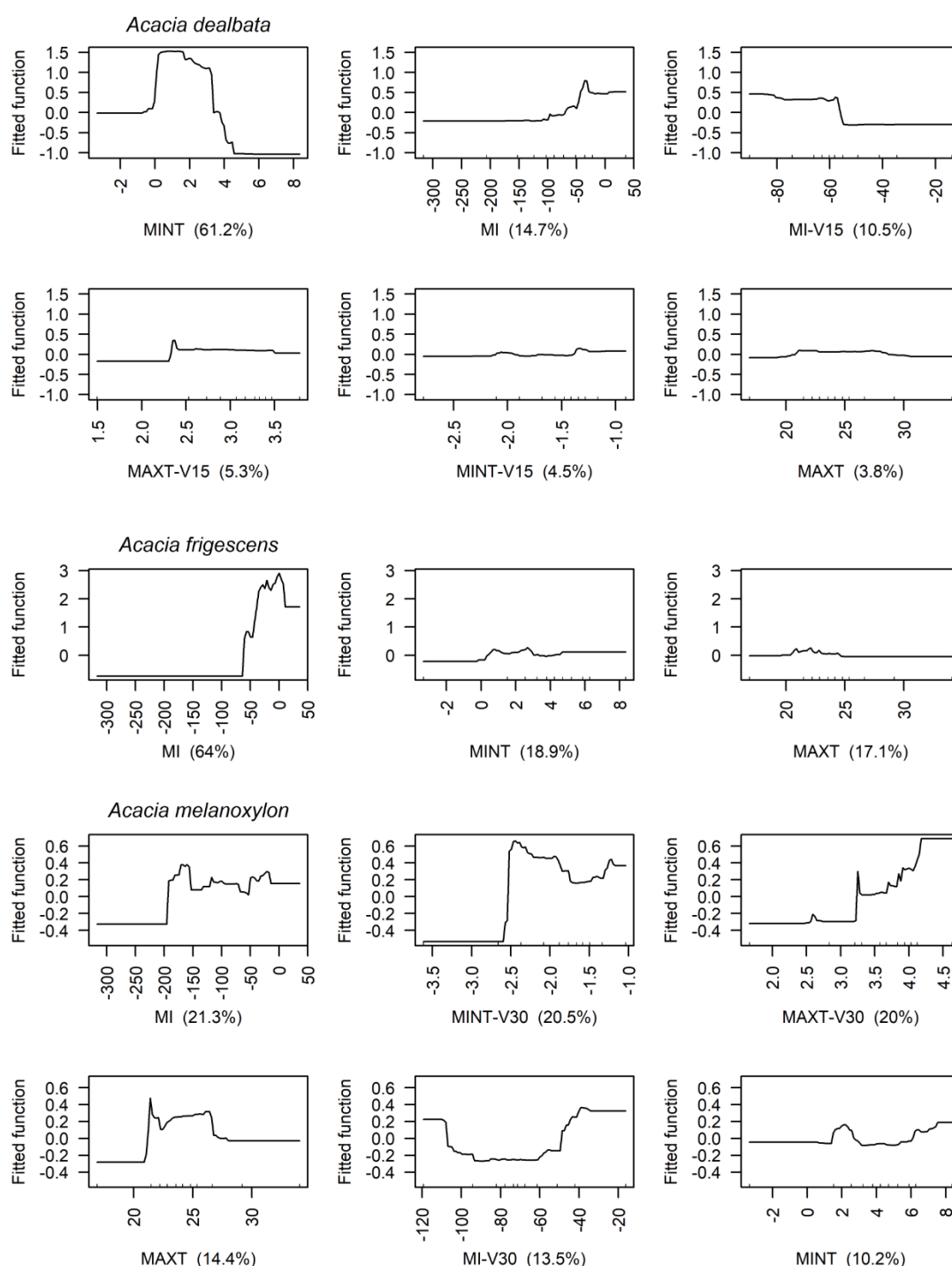


Figure 4.G.1: Species responses to extremes and interannual variability of maximum temperature (MAXT; MAXT-V_n), minimum temperature (MINT; MINT-V_n) and a moisture index (MI; MI-V_n) across Victoria, southeast Australia using the best performing model. Expected return interval in years indicated by n, or the scale parameter of the Generalised Extreme Value distribution (isotropic variability) when $n = \sigma$. Relative variable importance indicated in parenthesis on x-axis labels.

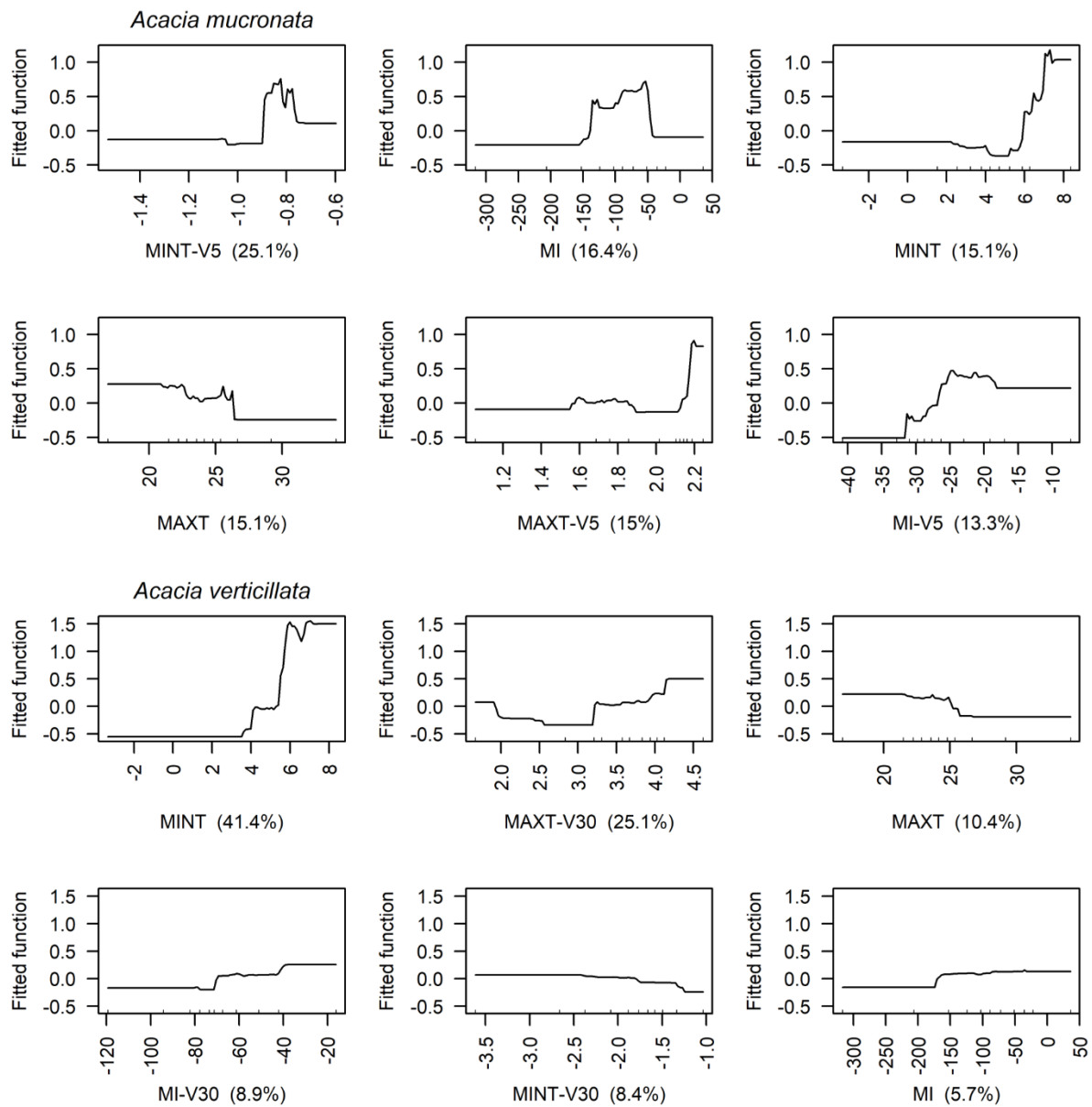


Figure 4.G.1: Continued.

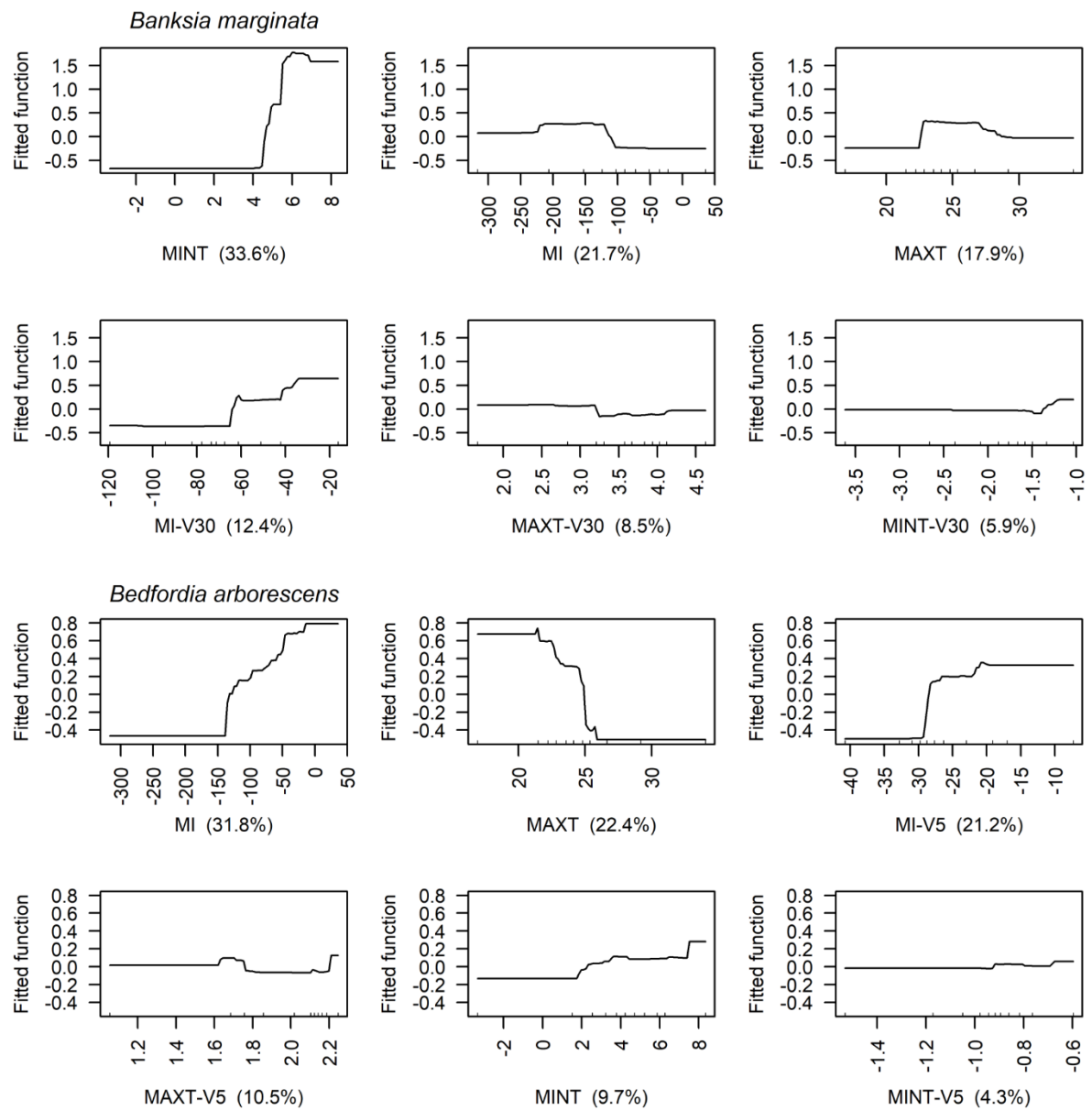


Figure 4.G.1: Continued.

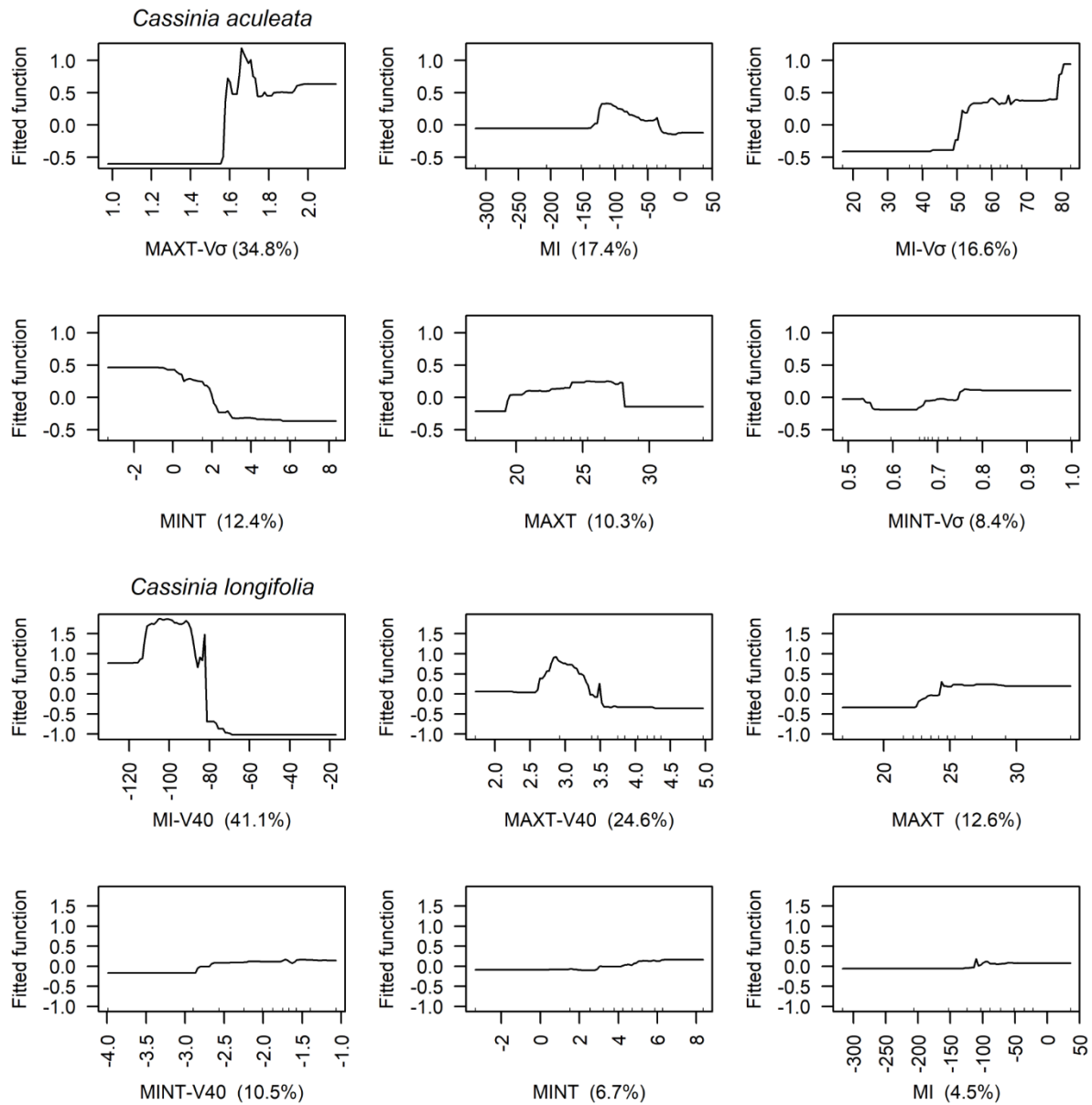


Figure 4.G.1: Continued.

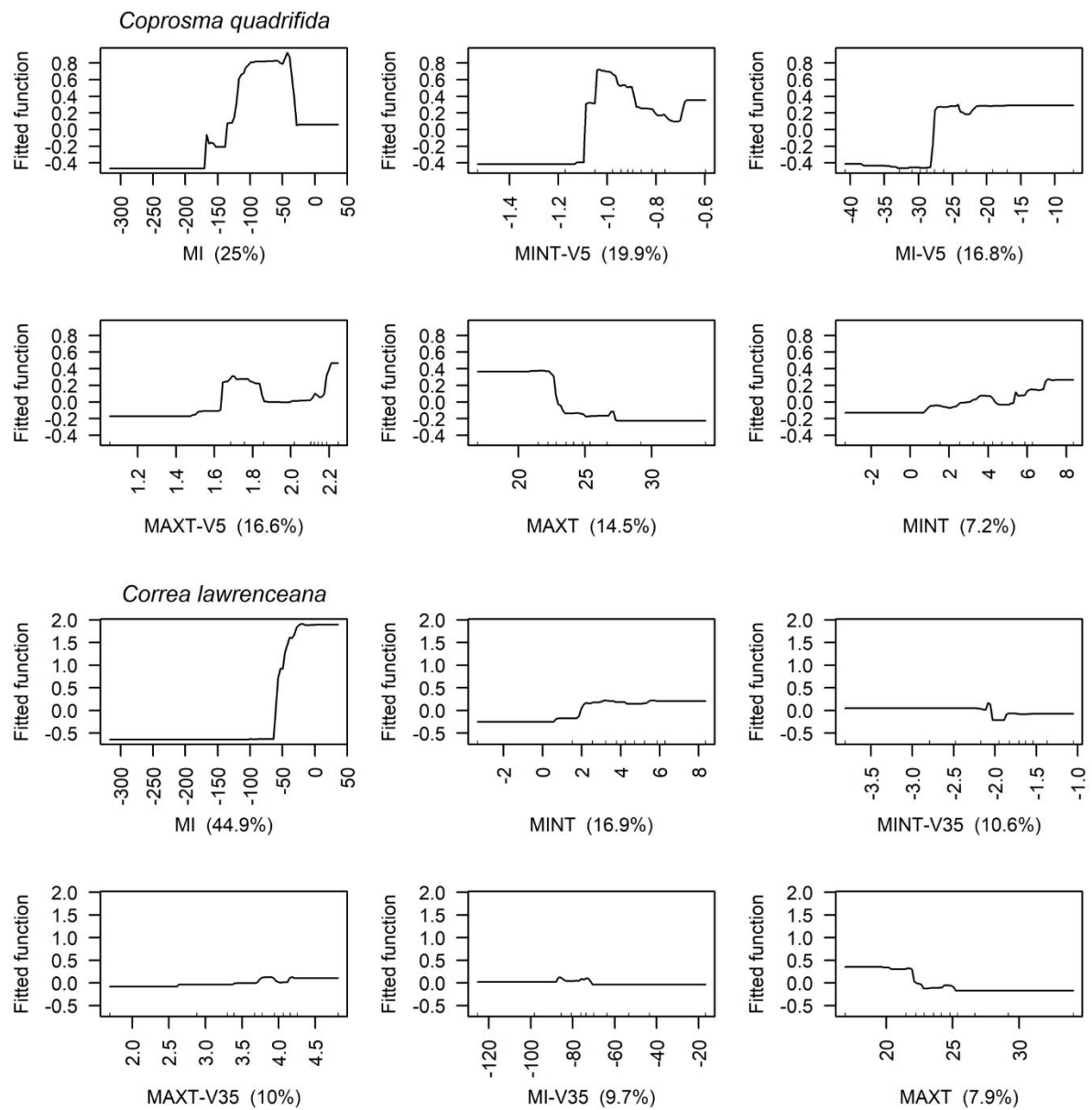


Figure 4.G.1: Continued.

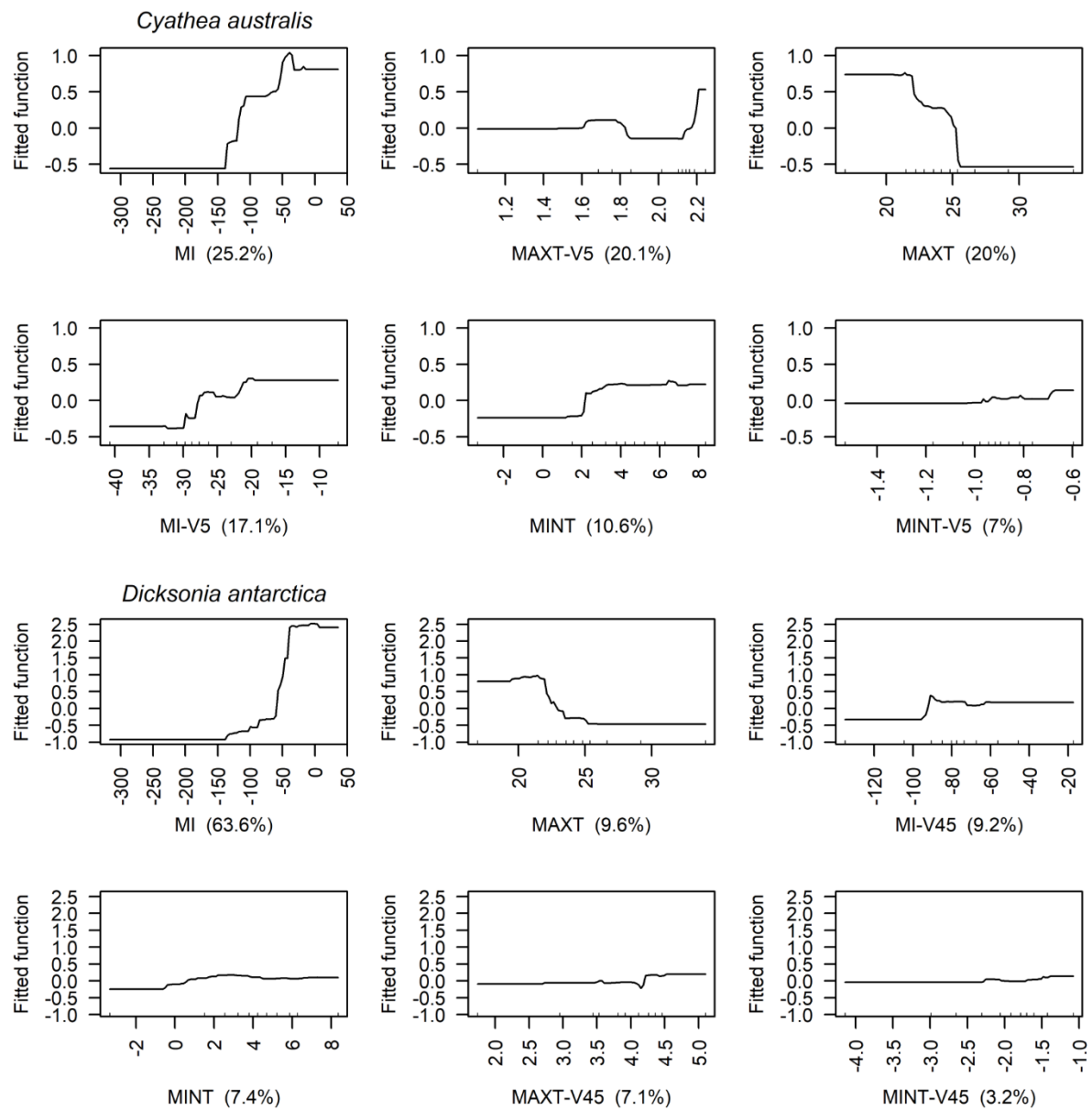


Figure 4.G.1: Continued.

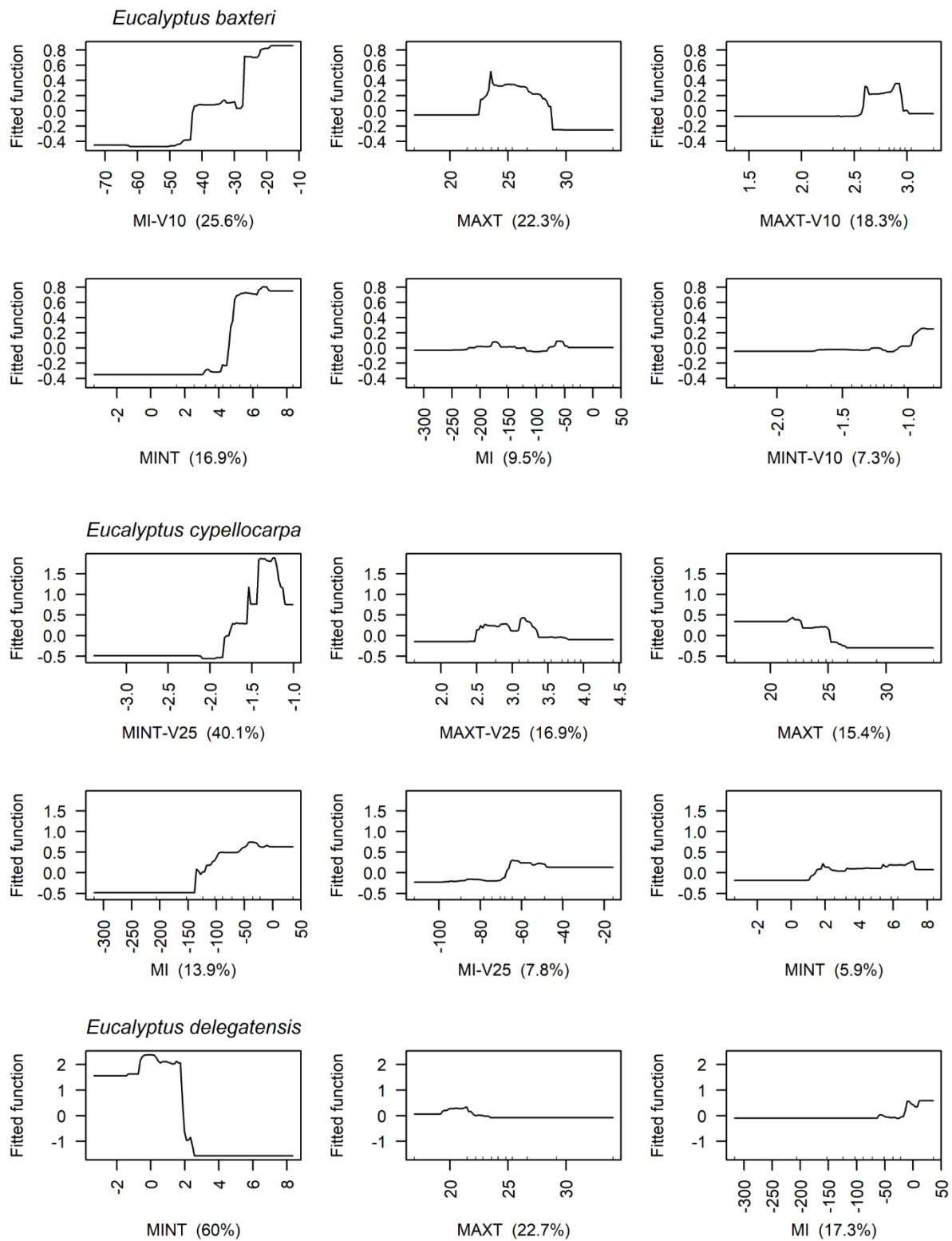


Figure 4.G.1: Continued.

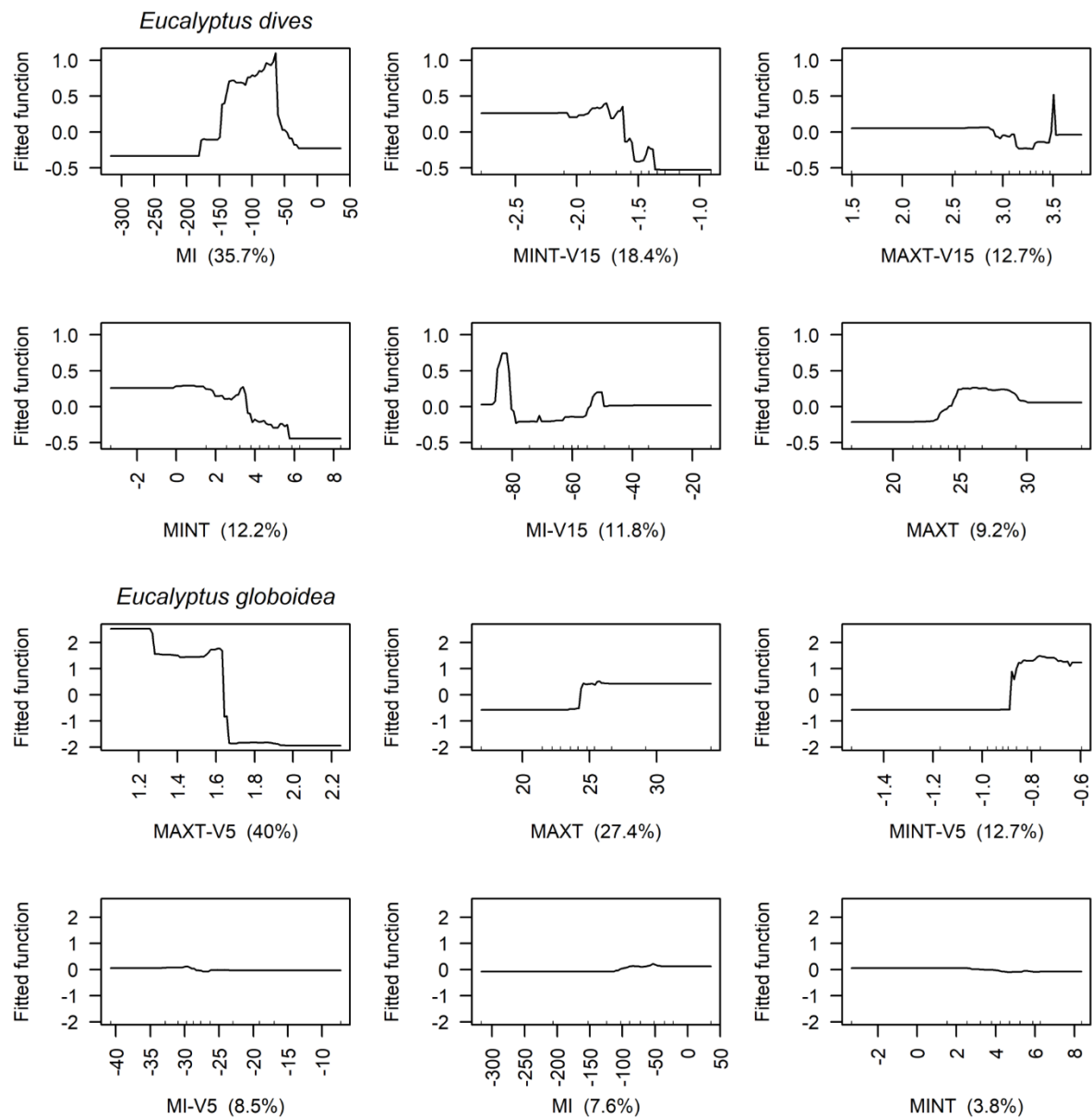


Figure 4.G.1: Continued.

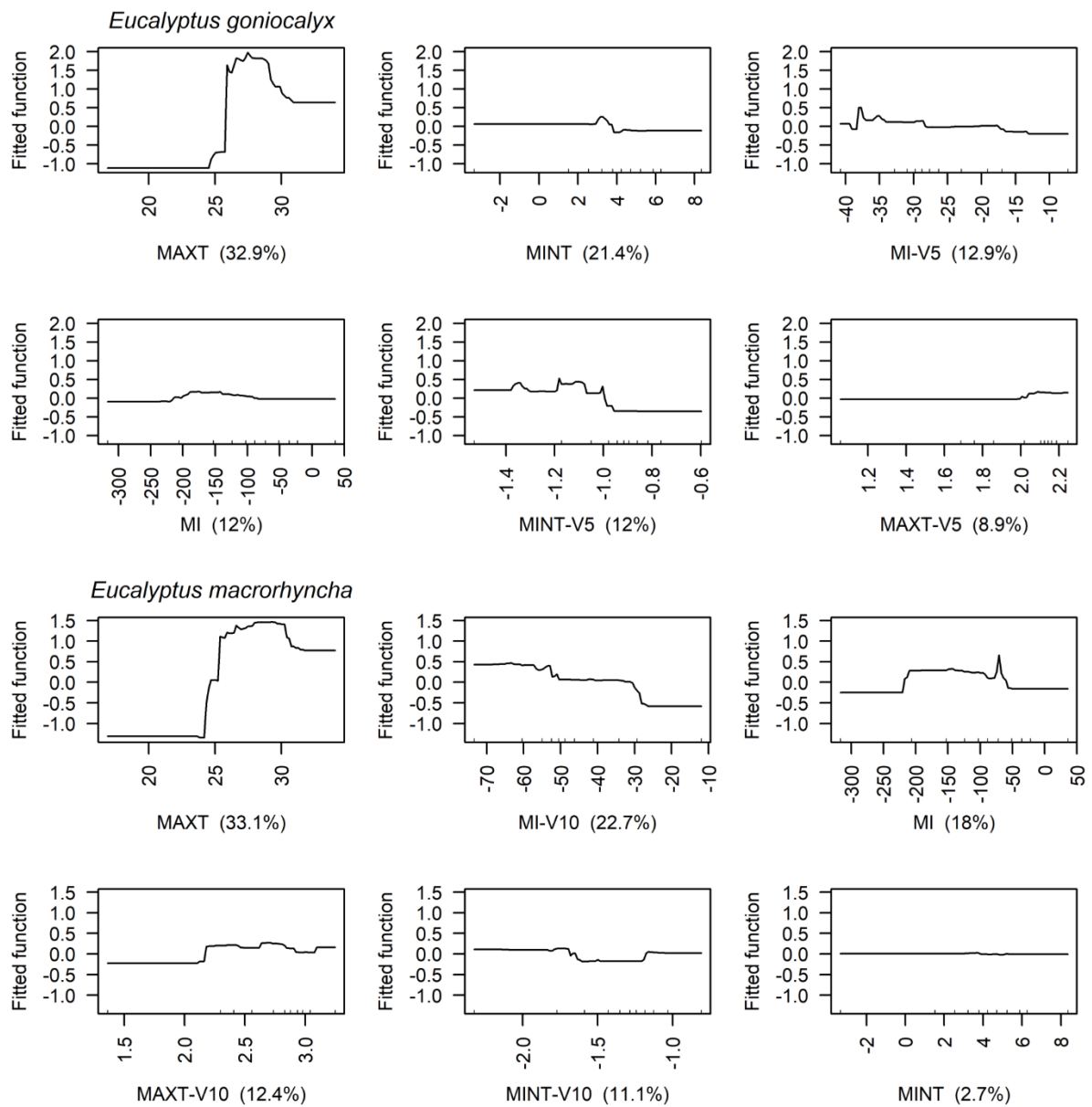


Figure 4.G.1: Continued.

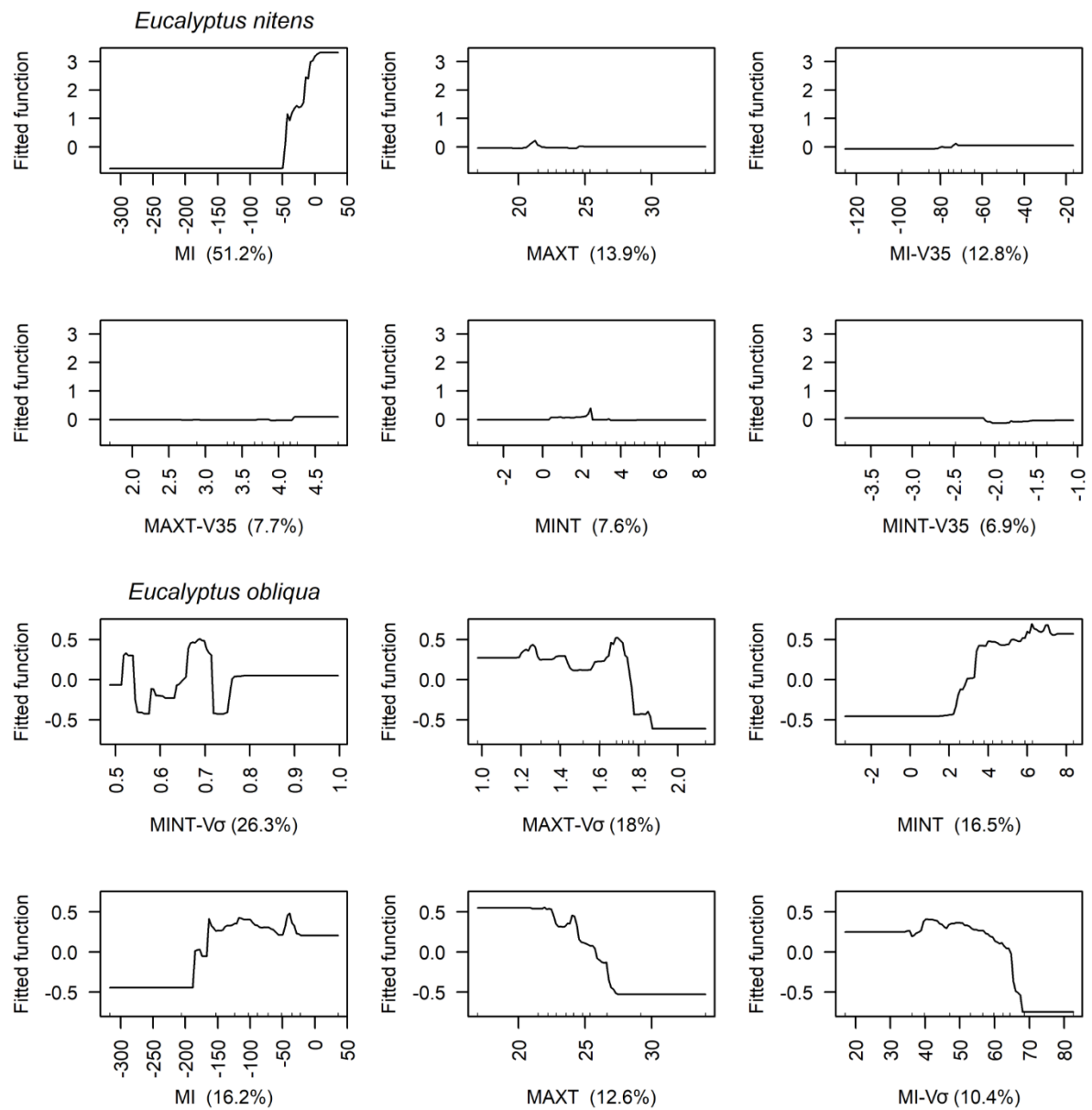


Figure 4.G.1: Continued.

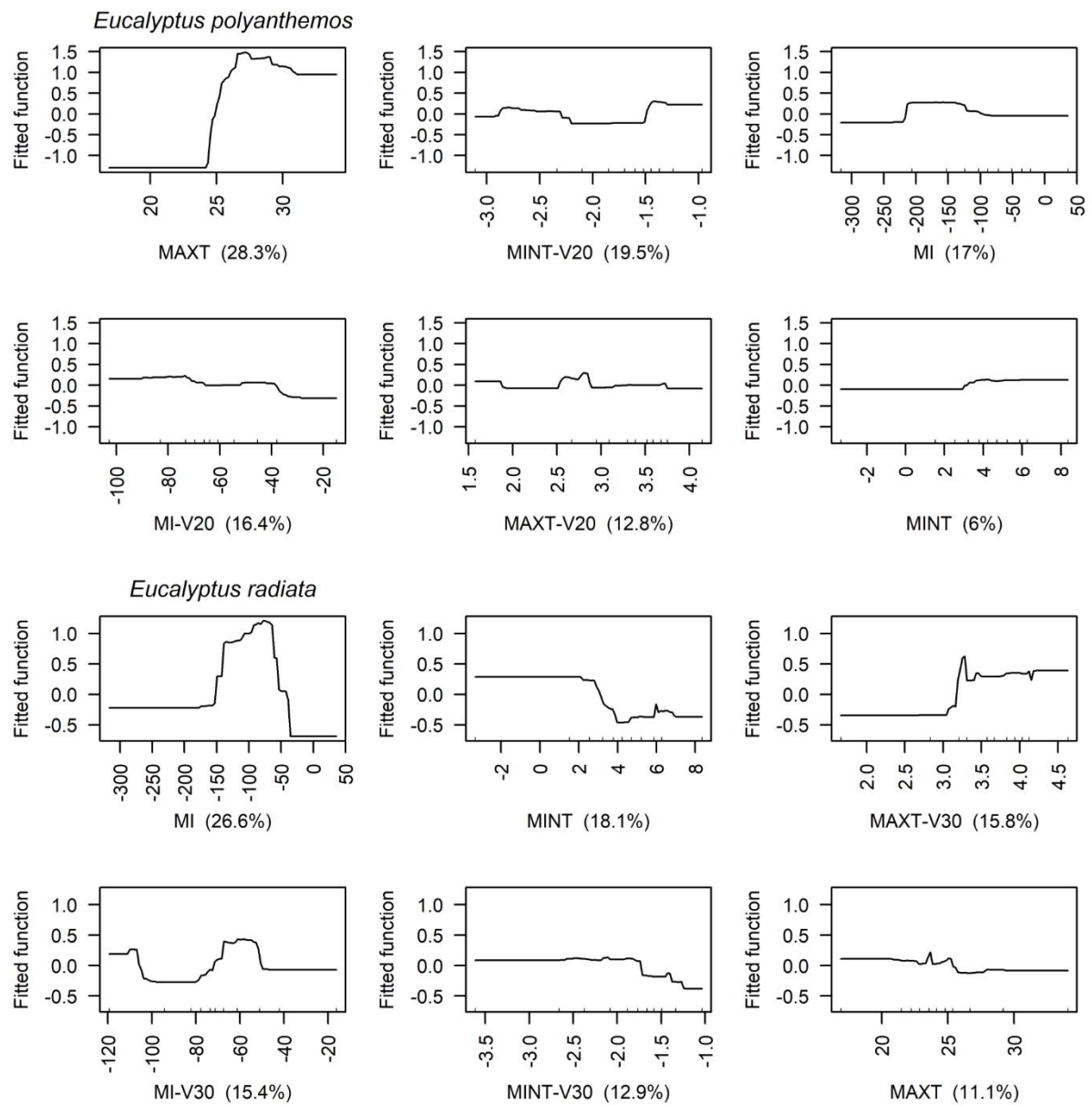


Figure 4.G.1: Continued.

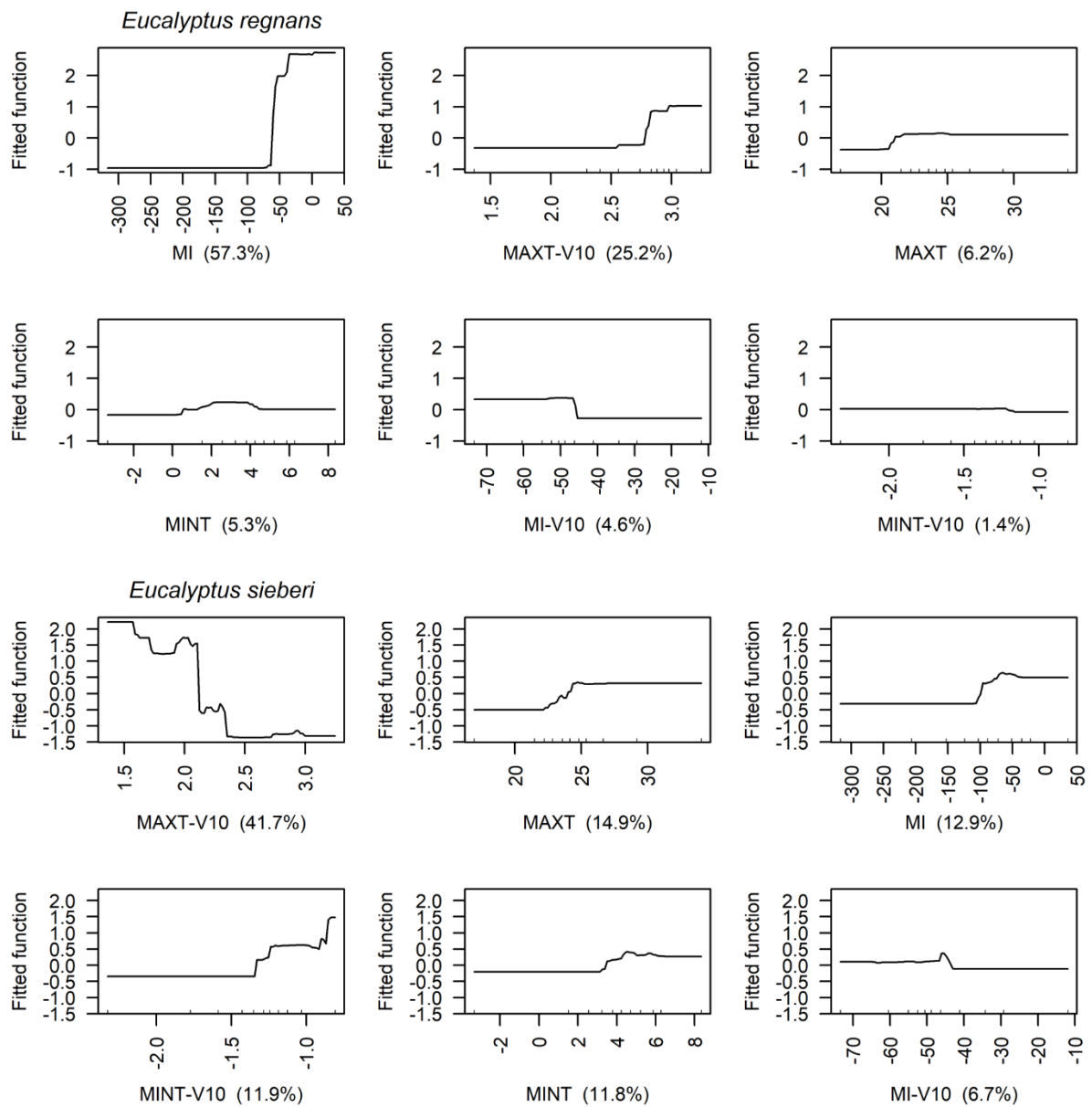


Figure 4.G.1: Continued.

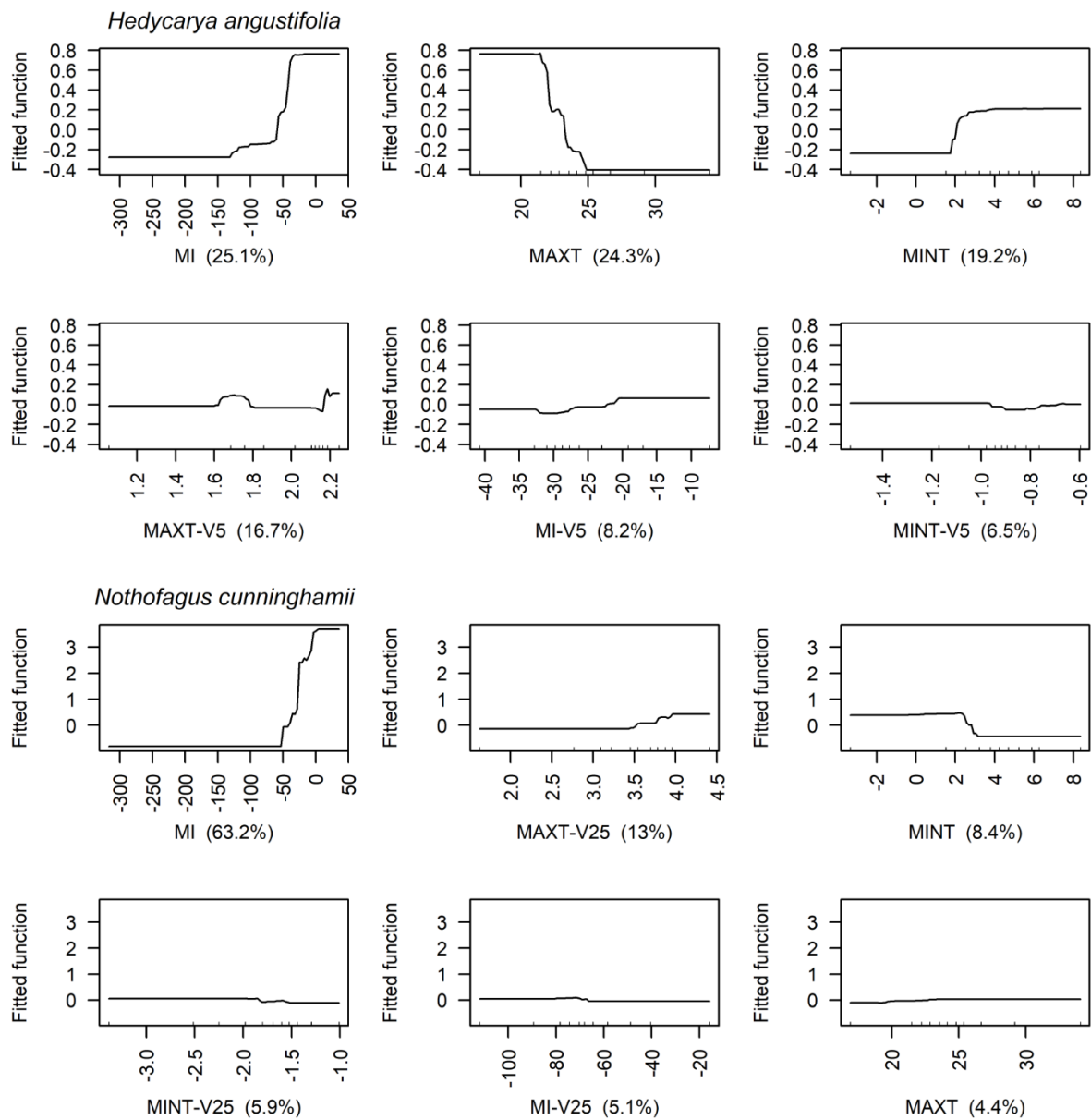


Figure 4.G.1: Continued.

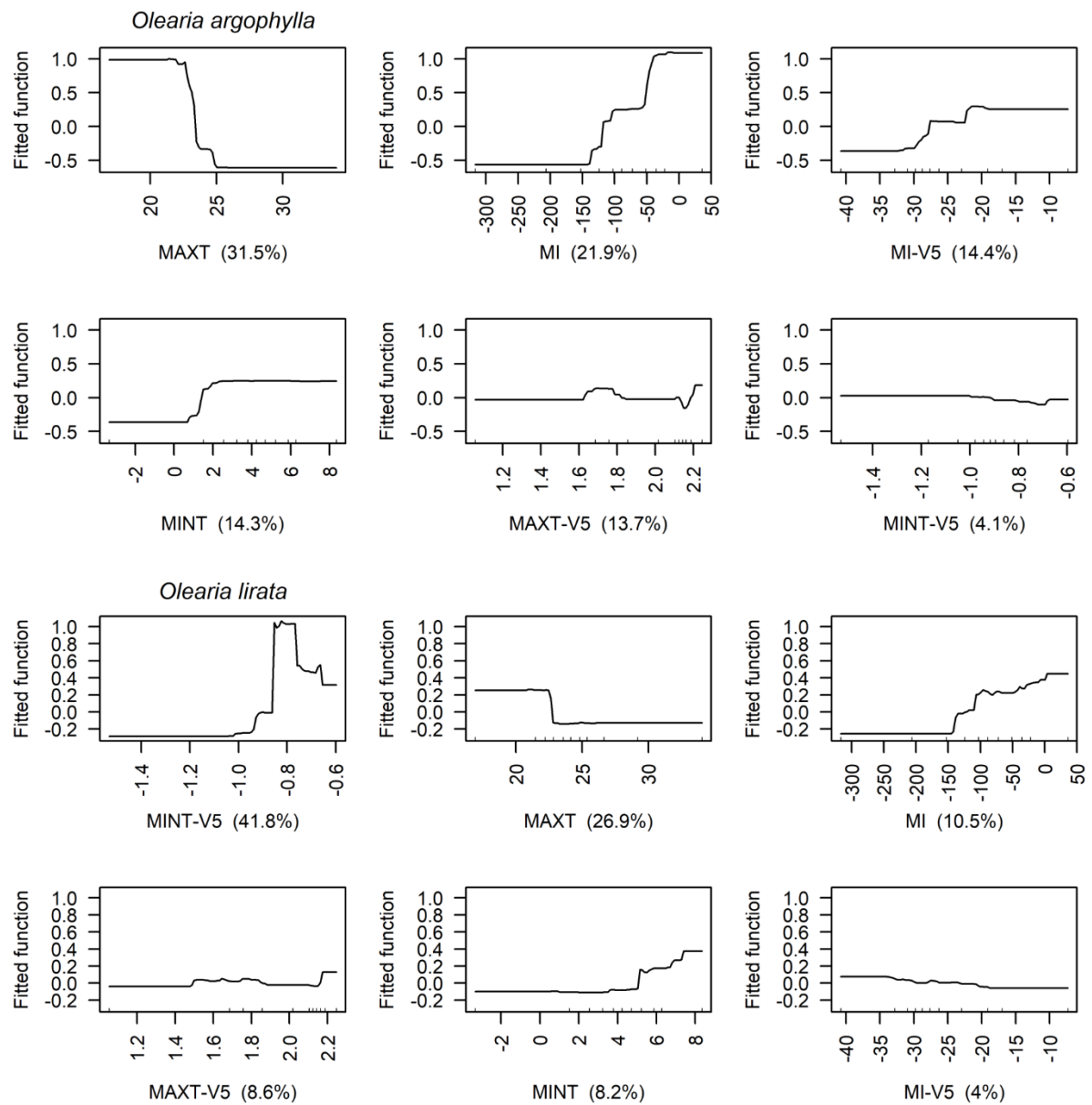


Figure 4.G.1: Continued.

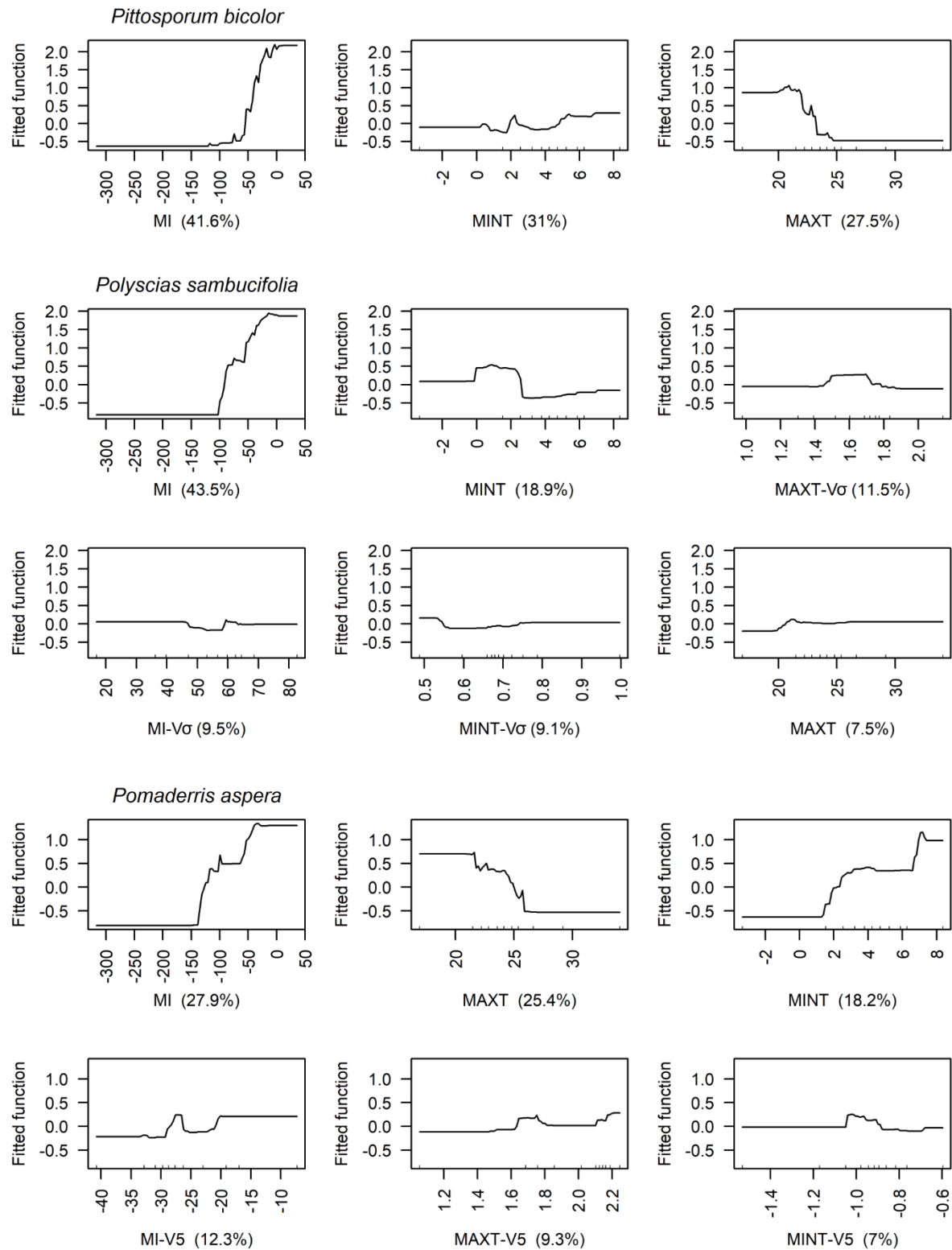


Figure 4.G.1: Continued.

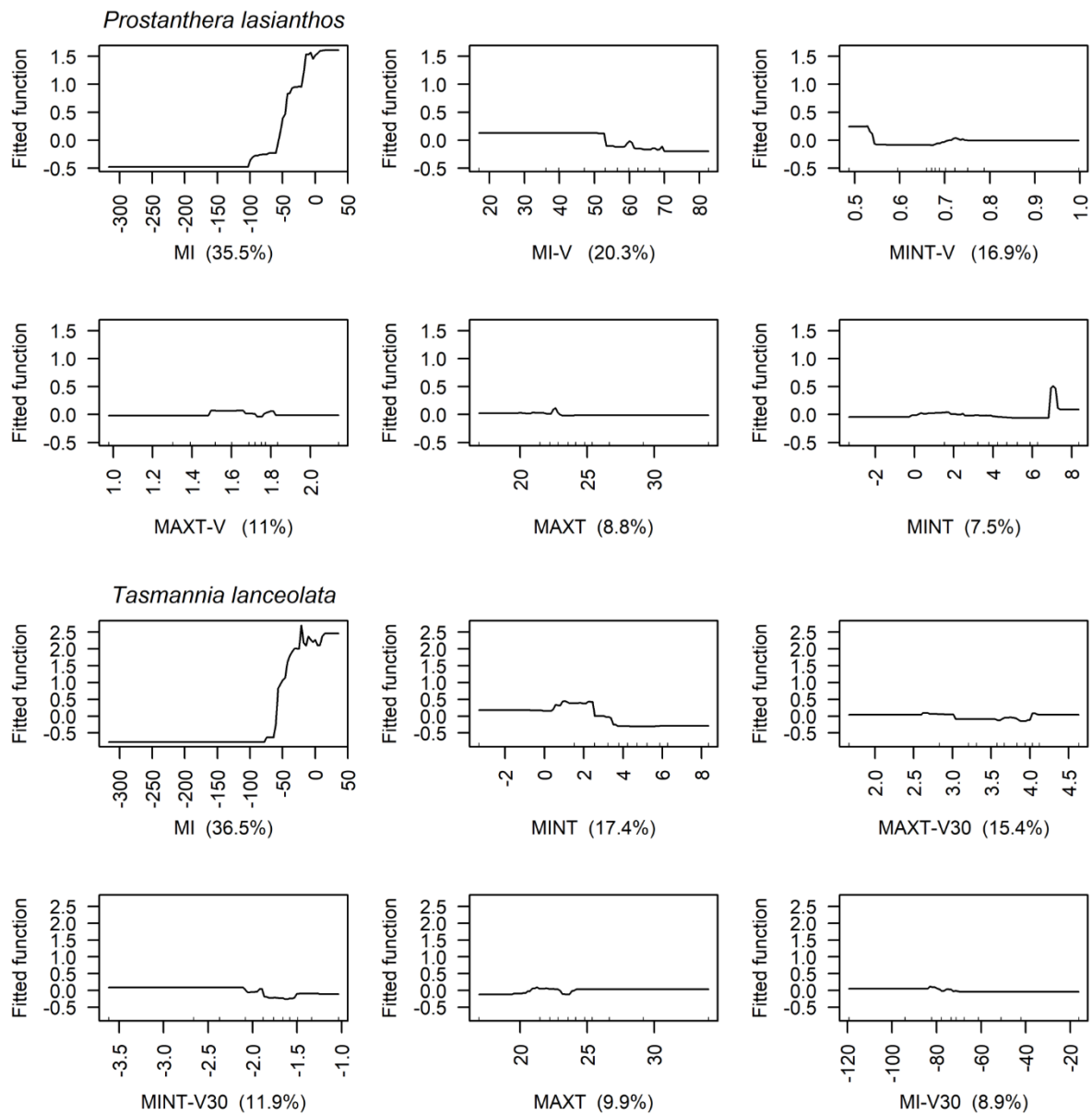


Figure 4.G.1: Continued.

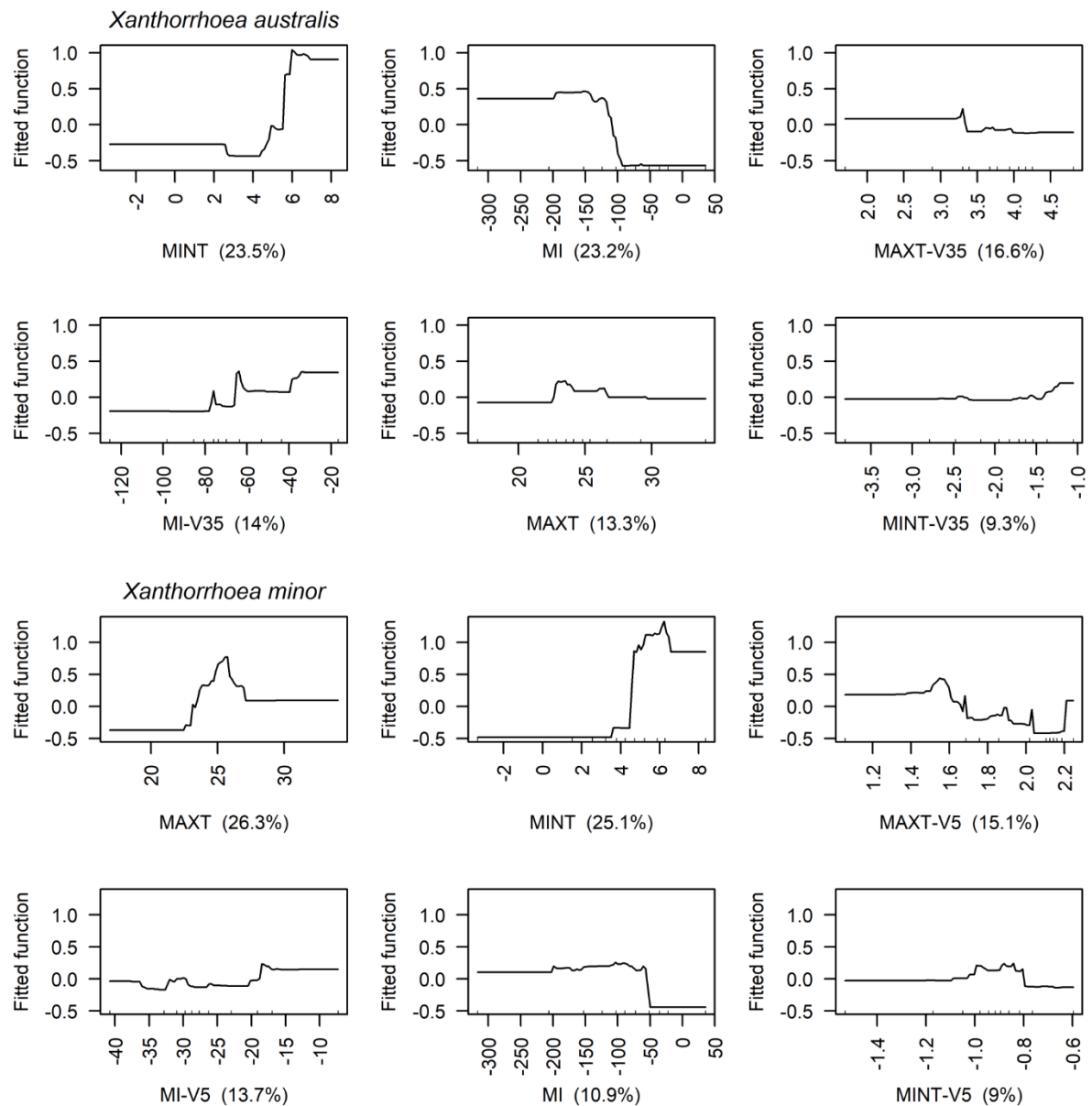


Figure 4.G.1: Continued.

APPENDIX 4.H: CHANGE IN THE SPATIAL DISTRIBUTION AND PERFORMANCE (D^2) OF PREDICTED SPECIES PROBABILITIES ACROSS VICTORIA USING MAXIMUM TEMPERATURE, MINIMUM TEMPERATURE AND MOISTURE INDEX EXTREMES (MEX) WITH VARIABILITY IN EXTREMES DERIVED FROM RETURN INTERVALS OF n YEARS ($n = 5, 10, \dots, 50$).

Please refer to the animated gif files provided as part of the digital appendices.

5

CHAPTER FIVE: EVALUATING DISPARATE CLIMATE DATASETS FOR PREDICTING PLANT SPECIES DISTRIBUTIONS

This chapter investigates the importance of climate dataset selection for modelling species distributions. The proliferation of global climate datasets in recent years means that there are many to choose from when building ecological models, yet comparisons of their predictive performance remains rare. Each of the climate datasets generated for Victoria and two versions of WorldClim were used to compare distribution models fitted for each of the 37 plant species selected in the previous chapter. Individual models were compared against one another and as ensembles to explore the potential for alternate predictions to complement one another. Two new metrics designed to support the interpretation of ensemble predictions were also developed as part of the analyses.

5.1. INTRODUCTION

Species distribution models (SDMs) are among the most widely used tools in ecology. These models link the presence, abundance or vital rates (e.g. growth rate, fecundity) of species to environmental conditions, typically with the use of spatial prediction surfaces. Among the earliest applications were simple methods such as BIOCLIM which the environmental envelope of a species based on where it is known to persist (Nix 1986; Booth et al. 2014). Since these early applications numerous methods of varying complexity have been developed to describe the spatial distribution of select species and biological communities (Sutherst 2003; Elith et al. 2006; Austin 2007; Ferrier et al. 2007; Elith et al. 2008; Kearney & Porter 2009; Mok et al. 2012; Mateo et al. 2017). The conceptual and practical issues surrounding SDMs have been explored from a wide variety of perspectives; however, the underlying uncertainty in climatic predictors is often overlooked (Bedia et al. 2013; Stoklosa et al. 2015; Baker et al. 2016; Baker et al. 2017; Suggit et al. 2017). Recent decades have seen a rapid increase in the

availability of high-resolution spatial datasets, often derived from remote sensing technologies which can characterise environmental conditions at broad scales. While many of these datasets provide new opportunities to directly estimate environmental gradients such as vegetation cover and vertical structure (e.g. Fedrigo et al. 2018, Fedrigo et al. 2019) there have also been ongoing efforts to enhance climate surfaces (e.g. Stewart & Nitschke 2017/Chapter 2; Stewart et al. 2017/Chapter 3; Fick & Hijmans 2017) which are critical inputs for a wide range of ecological models.

The development of new methods for representing climatic conditions and weather at fine scales has often been driven by the need to better understand vegetation distributions and ecological systems (Hijmans et al. 2005; Ashcroft & Gollan 2012; Booth et al. 2014; Kearney et al. 2014; Krager et al. 2017). Advances in computing and spline interpolation techniques (Wahba & Wendelberger 1980; Hutchinson & Bischof 1983) were crucial to the development of BIOCLIM in the late 80s and early 90s (Booth et al. 2014) and continue to provide effective methods for generating climate surfaces using weather station observations (Jeffrey et al. 2001; Hijmans et al. 2005; Hutchinson 2009, Hutchinson & Xu 2013; Stewart & Nitschke 2017/Chapter 2; Stewart et al. 2017/Chapter 3; Fick & Hijmans 2017; Xu et al. 2018; Fedrigo et al. 2019). The WorldClim datasets (Hijmans et al. 2005; Fick & Hijmans 2017) represent global climate and bioclimatic indices (see Booth et al. 2014) between 1950 and 2000 at relatively high resolution (approx. 1 km) and were recently updated to utilise additional covariates and remote sensing variables. WorldClim is one of the most widely used sources of climate data for ecological studies; however, many alternate methods of generating such datasets have been demonstrated at ecologically meaningful scales. These include downscaling and empirical adjustment of pre-existing climate surfaces (Kriticos et al. 2012; Kearney et al. 2014; Karger et al. 2017; Poggio et al 2018), correlative interpolations calibrated using micro-loggers in forested ecosystems (Ashcroft & Gollan 2012; Meineri & Hylander 2016), and techniques that build upon geostatistical and spline-based methods using high resolution earth observation data (Hengl et al. 2012; Oyler et al. 2014; Funk et al. 2015; Stewart & Nitschke 2017/Chapter 2; Stewart et al. 2017/Chapter 3).

Several studies have investigated alternate climate datasets representing current conditions and their impact on SDMs. These analyses have been conducted at a range of scales (from 50 m to 50 km), with various taxonomic groups, study regions, modelling algorithms and datasets, with and without consideration of climate change scenarios. High resolution

datasets which better characterise regional temperature and precipitation have been shown to provide better predictions relative to WorldClim when modelling the distributions of European beech (*Fagus sylvatica*) in Northern Iberia (Bedia et al. 2013), plant species in Switzerland (Kraeger et al. 2017), and several bird and fern species in the humid montane forests of Bolivia (Soria-Auza et al. 2010). Fine scale (50 m grid cells) temperature interpolations achieved similar predictive performance to WorldClim when modelling the current distribution of vascular plants in Sweden (Meineri & Hylander 2016), but the predicted extent and location of suitable habitat diverged considerably under alternate future climate scenarios. Distribution models for 451 plant species calibrated using six combinations of global climate data across central Africa, western India, and the Amazon basin were found to predict best when land surface temperature or precipitation derived from earth observation data were independently used as model covariates (Deblauwe et al. 2017). Baker et al. (2016) compared six alternate global climate datasets in their study of over 800 African bird species and found that the choice of climate data used in the baseline was at least as important, but could be much more important, as the choice of General Circulation Model (GCM) used for evaluating potential climate change. Each of these studies highlight the sensitivity of ecological models to climate dataset selection and demonstrate the need to develop robust approaches to quantifying uncertainty.

Aside from the examples listed above and those that address climate change scenarios (e.g. Araújo et al. 2005; Araújo & New 2007; Garcia et al. 2012; Thuiller et al. 2019), few SDM studies have directly considered how uncertainty in climate variables influence prediction. Part of the challenge is that there are many potential compounding sources of uncertainty (e.g. input data, algorithm selection and parameterisation) that can affect SDMs and climate surfaces. Stoklosa et al. (2015) demonstrated how uncertainty in the parameterisation of climate interpolations could drive bias in SDMs. While effective, this approach required concurrent climate interpolation (using a specific algorithm) and species modelling and therefore is not likely to be practical in most cases. Morales-Barbero and Vega-Álvarez (2018) recently proposed a method for characterising bias in the spatial predictions of species distribution models by fitting multiple global climate datasets in conjunction with a statistical measure of their congruence.

A more general approach to constraining prediction error which drives the success of many machine learning algorithms (e.g. Breiman 2001) and has been commonly applied in

climatology (Krishnamurti et al. 1999, Knutti et al. 2010) and species distribution modelling (Marmion et al. 2009), is to calculate the ensemble mean of competing models. Ensemble predictions will perform best when individual models have low bias and covariance, but high variance (Dormann et al. 2018); however, the potential for signal loss from specific predictions will in some cases favour the use of a single model over an ensemble (Knutti et al. 2010; Crimmins et al. 2013). Describing ensemble model performance using non-parametric methods such as cross-validation provides a reliable mechanism for evaluating uncertainty (Dormann et al. 2018); however, spatially continuous measures of ensemble behaviour are likely to be particularly useful in the case of climate dataset evaluation as embedded biases in model covariates may not always be detected in statistical performance metrics (Bedia et al. 2013).

The objectives of this research were to assess the impact of alternate climate datasets on modelled species distributions by comparing the statistical performance and spatial distribution of predictions both individually and as ensembles. It is important to understand how alternate climate baselines influence predictions for two primary reasons. Firstly, there are an increasing number of datasets becoming available and it may not always be clear which dataset is most suitable for a given application. Secondly, ecological models rely heavily on climate variables, and when they are projected into new space such as under climate change scenarios, they adopt the biases present in the selected baseline conditions. Three recently developed datasets for southeast Australia (Stewart & Nitschke 2017/Chapter 2) provide an opportunity to evaluate the influence that alternate climate interpolation techniques have on SDMs. These datasets were generated using identical station observations and widely adopted spline-based approaches (full dependence on latitude, longitude and elevation), in addition to partial dependence on topographic indices which characterise cold air pooling and drainage regimes, and remotely sensed land surface temperature (LST) data which can capture mesoscale temperature trends. We also considered the original WorldClim dataset (Hijmans et al. 2005) and version 2 which uses coastal proximity and LST to support the interpolation procedure (Fick & Hijmans 2017), as they provide an analogous comparison and are widely used in ecological studies. We first directly compare the statistical performance of models fitted using alternate datasets. Our analyses then consider how ensembles compare against individual models both statistically and spatially. We propose and demonstrate two non-parametric, spatially continuous measures of model congruence and uncertainty which complement and aid the interpretation of ensemble predictions.

5.2. METHOD

5.2.1. STUDY EXTENT AND SPECIES DATA

Plant species distributions were modelled across the extent of Victoria (141°-150°E, 34°-39°S), southeast Australia. Species data were collated from a range of systematically sampled plots collected as part of several field campaigns across a range of forested ecosystems in Victoria between 2006 and 2017 (see Chapter 4; Haslem et al. 2016; Kasel et al. 2017; Fairman et al. 2017; Chick et al. 2018; Haywood et al. 2018; Fedrigo et al. 2019). Species capable of reaching at least 3 m in height (to maximise detection probability), occurring across a range of climatic gradients and with at least 80 presence records available were selected for modelling ($n = 37$). These criteria were selected to build robust models for species across a range of niches. Sub-species were not indicated in many records, and therefore all data was aggregated to the species level. Only *Acacia verticillata* records included more than one subspecies (*subsp. verticillata* and *subsp. ovoidea*), but each share a similar geographic distribution (<https://vicflora.rbg.vic.gov.au/>).

5.2.2. CLIMATE VARIABLES

Spatial variables were generated using maximum temperature, minimum temperature and precipitation data from five distinct climate datasets. Three of these datasets were developed specifically for correlative and mechanistic ecological modelling in Victoria (Stewart & Nitschke 2017/Chapter 2). These were developed at high spatial (approx. 250 m) and temporal (daily, January 1981 to July 2014) resolution to capture variability in topographically complex landscapes. These permit calculation of derived variables summarising the time series in ecologically relevant ways (e.g. inter-annual distribution of extremes) for SDMs. The two WorldClim datasets (Hijmans et al. 2005; Fick & Hijmans 2017) were also used in the analysis given their widespread use in species distribution modelling and global coverage, though they only represent long-term mean conditions between 1950 and 2000. We used the monthly WorldClim values rather than the derived bioclimatic indices. CHIRPS precipitation data (Funk et al. 2015) was initially considered but subsequently excluded as local interpolations better represent precipitation across Victoria (Appendix 5.A). Each of the datasets selected use thin plate smoothing splines to interpolate climate records,

with various combinations of latitude, longitude, elevation, topographic indices, coastal proximity and thermal remote sensing data as either spline variables or independent linear covariates (Table 5.1).

Table 5.1: Description of climate datasets used for species distribution modelling in Victoria, southeast Australia. Each dataset is constructed using weather station observations interpolated using thin plate spline models. Variables within $f()$ are independent spline variables, followed by linear covariates for partial spline models.

Dataset	Maximum temporal resolution and range	Spatial Resolution	Maximum Temperature	Minimum Temperature	Precipitation
VECD ^{1,2,3}	Daily, monthly and monthly mean January 1981 to July 2014	0.0025° (approx. 250 m)	$f(x, y, \text{elevation})$	$f(x, y) + \text{elevation}$	$f(x, y, \text{smoothed elevation})$
VTCD ^{1,2,3}	Daily, monthly and monthly mean January 1981 to July 2014	0.0025° (approx. 250 m)	$f(x, y, \text{elevation})$	$f(x, y, \text{elevation}) + \text{topographic index}$	$f(x, y, \text{smoothed elevation})$
VTCD+M ^{1,2,3}	Daily, monthly and monthly mean January 1981 to July 2014	0.0025° (approx. 250 m)	$f(x, y, \text{elevation}) + 1 \text{ km MODIS LST}$	$f(x, y, \text{elevation}) + \text{topographic index} + 1 \text{ km MODIS LST}$	$f(x, y, \text{smoothed elevation})$
WorldClim ⁴	Monthly mean 1950 to 2000	0.008° (approx. 1 km)	$f(x, y, \text{elevation})$	$f(x, y, \text{elevation})$	$f(x, y, \text{elevation})$
WorldClim v2 ⁵	Monthly mean 1950 to 2000	0.008° (approx. 1 km)	$f(x, y, \text{elevation}, \text{distance to coast}, 5 \text{ km MODIS LST})$	$f(x, y, \text{elevation}, \text{distance to coast}, 5 \text{ km MODIS LST})$	$f(x, y, \text{elevation}) + \text{distance to coast}$

¹ Stewart & Nitschke 2017/Chapter 2; ² Fedrigo et al. 2019; ³ Chapter 4 ⁴ Hijmans et al. 2005; ⁵ Fick & Hijmans 2017

VECD = Victorian elevation-only climate dataset; VTCD = Victorian topo-climate dataset; VTCD+M = Victorian elevation plus MODIS climate dataset; x = latitude; y = longitude, MODIS LST = moderate-resolution imaging spectroradiometer land surface temperature.

Each dataset was used to generate a series of derived spatial prediction surfaces for species distribution modelling. An aridity index (based on de Martonne 1926) that could be calculated using the available variables from each dataset was used in place of precipitation to represent seasonal moisture availability. The quarterly moisture-heat index ($QHMI$) was calculated as:

$$QHMI_i = \frac{P_{sum,i}}{T_{mean,i} + 10}$$

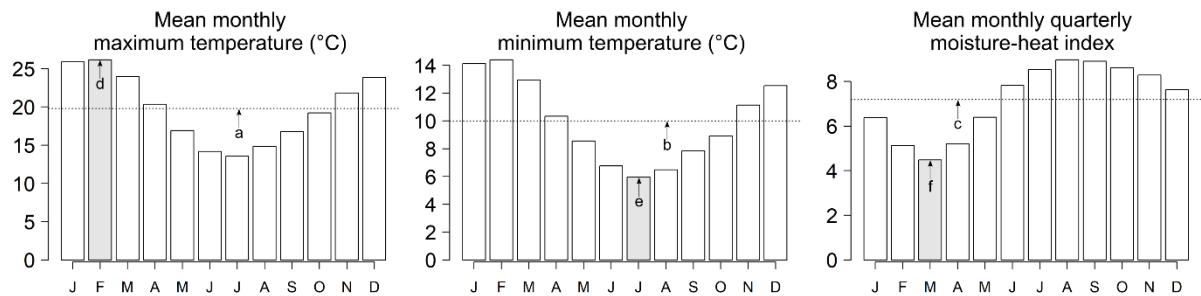
where P_{sum} is the total precipitation and T_{mean} is the mean temperature of the contiguous 3-month period i .

Annual mean minimum temperature, maximum temperature and *QHMI* were calculated for each monthly mean (MM) dataset ($n = 5$) along with corresponding measures of seasonality, which were designed to reflect the difference between mean annual conditions and the hottest, coldest and driest months of the year. Time-series variables were also generated for each of the Victorian datasets ($n = 3$) where seasonality and extremes were derived from Generalised Extreme Value (GEV) distributions (Coles 2001) for each variable. Extreme variables were calculated with expected return intervals of 20 years to ensure they could represent the temporal extent of the time-series (33 years), allow for a consistent approach, and had previously performed well for these species using return intervals between 5 and 50 years (Chapter 4). A detailed graphical description of the variables used for species distribution modelling and their calculation methods are illustrated in Figure 5.1.

Mean monthly climate variables (MM; 1981-2010 mean; $n = 6$ variables)

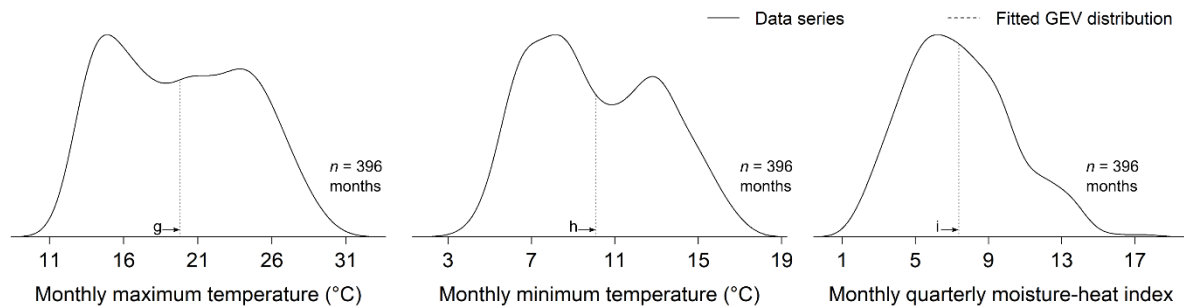
145.101°E 37.942°S

- Annual mean maximum temperature (a)
- Annual mean minimum temperature (b)
- Annual mean quarterly moisture-heat index (c)
- Maximum temperature seasonality (d - a)
- Minimum temperature seasonality (e - b)
- Quarterly moisture-heat index seasonality (f / c)



Time-series derived climate variables (TS; 1981-2014 monthly values; $n = 9$ variables)

- Annual mean maximum temperature (g)
- Annual mean minimum temperature (h)
- Annual mean quarterly moisture-heat index (i)
- Maximum temperature seasonality (j - g)
- Minimum temperature seasonality (k - h)
- Quarterly moisture-heat index seasonality (l / i)
- Maximum temperature extreme (m - j)
- Minimum temperature extreme (n - k)
- Quarterly moisture-heat index extreme (o / l)



Extremes extracted and fitted to Generalised Extreme Value (GEV) distributions

Extremes defined as maximum temperature of warmest month (d), minimum temperature of coldest month (e) and minimum quarterly moisture-heat index of the driest month (f) for each year in the time series

Tail centre, the location parameter of the GEV distribution (j,k,l)

Tail edge, corresponding to 1 in 20 year extreme (m,n,o)

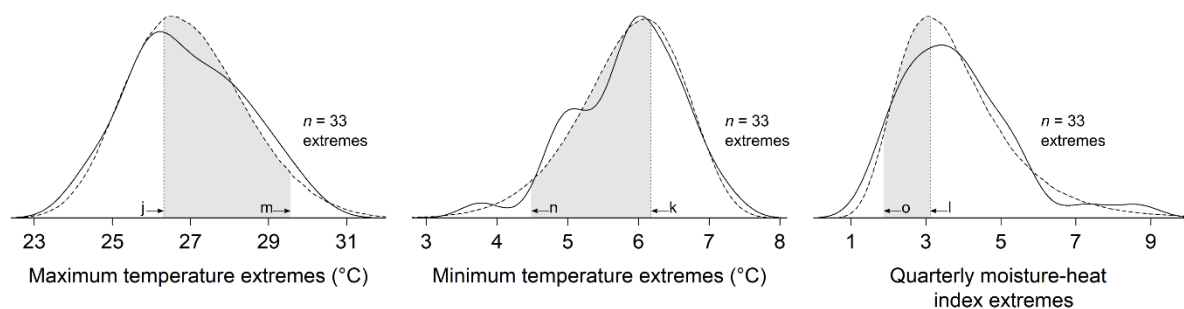


Figure 5.1: Climate variables derived from monthly mean (MM; $n = 6$) and monthly time-series (TS; $n = 9$) datasets used for species distribution modelling. Data represents a single site southeast of Melbourne, Australia.

5.2.3. SPECIES DISTRIBUTION MODELLING AND PERFORMANCE

Species distribution models were fitted using boosted regression trees (see Elith et al. 2008) and evaluated following the methods described in our previous analysis of extreme predictors (Chapter 4). All models were fitted using the `gbm.step` function of the `dismo` package in R (Hijmans et al. 2017; Ridgeway 2017). Model performance was primarily evaluated using the proportion of deviance explained (D^2) on cross-validated predictions. A spatially blocked cross-validation design was applied across a 1° grid to minimise the underestimation of prediction error linked to spatial autocorrelation (Roberts et al. 2016; Schratz et al. 2019) using the `blockCV` package in R (Valavi et al. 2018). Cross-validation folds were held constant across all models for each species.

Pairwise comparisons of cross-validated model performance were performed between all combinations of climate predictor sets using two-tailed t-tests. Additive improvements in model performance were evaluated with ensemble means of cross-validated model predictions calculated for various groups of models (i.e. both WorldClim models, MM, TS or all Victorian models, all VECD models, all VTCD models, all VTCD+M models, and all models combined). Each of the contributing models were assigned equal weight to avoid the introduction of additional unknown biases (Claeskens et al. 2016). Ensemble means were compared against individual models using one-sided pairwise t-tests based on the hypothesis that they would provide an improvement in model performance. All p values derived from the pairwise t-tests were adjusted for multiple comparisons using the Holm-Bonferroni method.

Spatial predictions were made for each species and set of climate predictors across the full extent of Victoria. Predictions derived from the WorldClim surfaces were resampled to the same resolution as the Victorian datasets (0.0025° , approx. 250 m) using nearest neighbour interpolation. Ensemble means of predictions from all eight climate datasets for each species were calculated using the final gridded datasets. Individual prediction surfaces were retained to allow for the calculation of model congruence and uncertainty metrics.

5.2.4. MODEL CONGRUENCE AND VARIABILITY

Multi-model ensembles contain a large amount of information that is lost when calculating a mean prediction surface. Statistical methods for summarising the distribution of separate model predictions were used in developing two new metrics to support the interpretation of ensembles. These metrics were designed around the concept of a threshold that optimally classifies predictions into binary categories (i.e. suitable or unsuitable in SDM). SDM predictions only classified into binary surfaces in certain situations due to the loss of information that occurs and therefore these thresholds are not always useful. The proposed metrics instead rely upon the *distance* from this optimal threshold to characterise contributing model behaviour. The statistical properties of this distance may be used to describe agreement of individual predictions around the threshold value and therefore indicate where the ensemble may be most sensitive to disparate predictions. Both variables are derived from the Chebyshev–Cantelli inequality (Cantelli 1911), which is insensitive to the distribution of data (i.e. no requirement for normality). Continuous, pixel-level measures of model congruence and uncertainty were derived for each species as a function of the probabilities predicted by each individual model in the ensemble.

The optimal classification threshold T is first obtained by calculating the mean threshold that maximises the sum of sensitivity (true positive rate) and specificity (true negative rate) using spatially blocked cross-validated predictions from each of the contributing models. This criteria for identifying the optimal threshold was selected based on the recommendations of Jiménez-Valverde & Lobo (2007) but could be estimated by other means (e.g. maximise Kappa). The Standard Threshold Score (STS) is then calculated for all pixels as

$$STS_j = \frac{\mu_j - T}{\sigma_j}$$

where μ and σ are the mean and population standard deviation of modelled probabilities across all contributing models at pixel j . The STS calculations provide a spatially continuous surface which express the ensemble mean prediction in standard deviations from T .

The Chebyshev–Cantelli inequality (Cantelli 1911)

$$P(X - \mathbb{E}[X] \geq k) \leq \frac{\sigma^2}{\sigma^2 + k^2}$$

gives the probability that random variable X will be greater than k standard deviations from the mean (Figure 5.2) was used to calculate the Threshold Agreement Index (TAI), which describes the degree that individual models agree above or below the optimal classification threshold. The TAI is calculated as

$$TAI = \begin{cases} \left(\frac{1}{1 + STS^2} \right) - 1 & \text{if } STS < 0 \\ 1 - \left(\frac{1}{1 + STS^2} \right) & \text{if } STS \geq 0 \end{cases}$$

such that the sign of the difference from the threshold is preserved and values are bound between -1 and 1. For example, TAI values of -0.8 ($STS = -2$) or 0.8 ($STS = 2$) indicate that a minimum of 80% of the individual model probabilities are below or above the selected threshold, respectively.

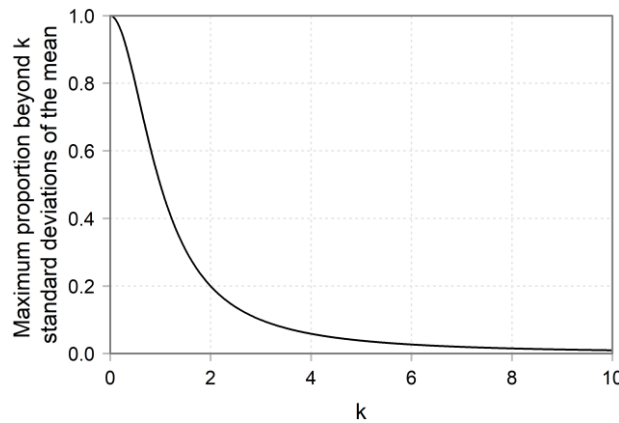


Figure 5.2: The maximum proportion of values beyond k standard deviations of the mean as per the Chebyshev–Cantelli inequality (Cantelli 1911).

The Threshold-scaled Standard Deviation (TSD) uses the STS to scale variability of contributing model predictions around the optimal threshold. This penalises prediction variability in regions where there is strong agreement for suitable or unsuitable environmental conditions and emphasises variability in model predictions closest to the ensemble threshold. The TSD is calculated as

$$TSD = \frac{\sigma}{1 + STS^2}$$

5.3. RESULTS

Each of the Victorian datasets achieved significant ($p < 0.05$; $n = 4$) or marginally significant ($p < 0.1$; $n = 2$) improvements in D^2 when compared against the original WorldClim dataset, all estimated on held-out test data in the block cross-validation (Table 5.2). While the Victorian datasets achieved higher D^2 on average relative to WorldClim v2, these differences were not statistically significant after adjusting for multiple comparisons. No statistically significant differences were found between the two WorldClim datasets, although v2 did perform better on average. The Victorian climate datasets achieved a similar level of performance; though there were differences from species to species. Overall, the monthly mean VECD model achieved higher D^2 on average relative to all other models. Cross-validated D^2 and AUC for each species and set of climate variables are tabulated in Appendix 5.B.

Table 5.2: Mean pairwise percentage differences in the proportion of deviance explained across plant species ($n = 37$) distribution models fitted using discrete monthly mean (MM) or time-series (TS) climate datasets. Statistical comparisons performed using two-tailed pairwise t-tests with Holm-Bonferroni adjustment for multiple comparisons. Note that statistical differences do not always correspond to the magnitude of mean pairwise percentage differences due to dispersion in the results.

	WC1 (MM) ¹	WC2 (MM)	VECD (MM)	VTCD (MM)	VTCD+M (MM)	VECD (TS)	VTCD (TS)
WC2 (MM)²	8.5	–	–	–	–	–	–
VECD (MM)^{3,4}	17.3**	8.2	–	–	–	–	–
VTCD (MM)^{3,4}	15.4***	6.4	-1.6	–	–	–	–
VTCD+M (MM)^{3,4}	13.5**	4.7	-3.2	-1.6	–	–	–
VECD (TS)^{3,5}	14.2*	5.3	-2.7	-1.1	0.5	–	–
VTCD (TS)^{3,5}	14.6*	5.7	-2.3	-0.6	1.0	0.4	–
VTCD+M (TS)^{3,5}	16.1**	7.1	-1.0	0.6	2.3	1.7	1.3

¹ Hijmans et al. 2005; ² Fick & Hijmans 2017; ³ Stewart & Nitschke 2017/Chapter 2; ⁴ Fedrigo et al. 2019; ⁵ Chapter 4.

WC1 = WorldClim, WC2 = WorldClim v2; VECD = Victorian elevation-only climate dataset; VTCD = Victorian topo-climate dataset; VTCD+M = Victorian elevation plus MODIS climate dataset.

Statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Ensembles were formed using different combinations of models (Table 5.3, rows). Most ensemble means of cross-validated model predictions achieved highly significant ($p < 0.01$) improvements in statistical performance relative to each of the individual models across

all species (Figure 5.3; Table 5.3). The level of increase achieved was greatest for the original WorldClim dataset, followed by WorldClim v2 and the remaining Victorian datasets. Both WorldClim datasets were significantly improved by taking the mean of their predictions (μ WC, Table 5.3); however, this did not provide a significant improvement over any of the individual Victorian datasets. The ensemble of monthly mean datasets for Victoria performed better than each of the individual monthly mean models; however, improvements relative to the time-series derived models were at best marginally significant ($p < 0.1$, $n = 2$) despite being better on average. Conversely, the ensemble of time-series datasets performed better than each of the individual time-series models but did not provide a significant improvement over the individual monthly mean variants. The performance improvement obtained by the ensemble of all models, or all models fitted with Victorian datasets on average demonstrate cumulative additive improvements relative to any of the individual models assessed.

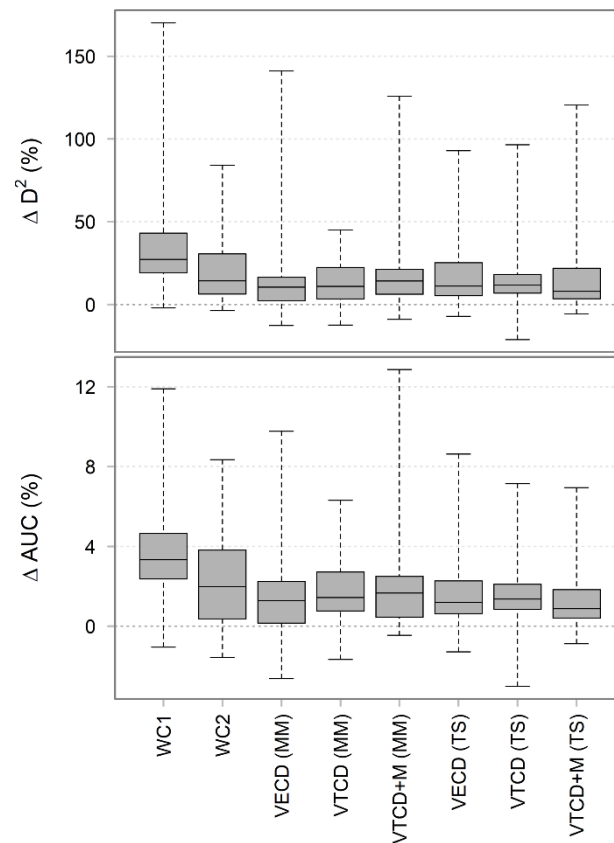


Figure 5.3: Mean pairwise percentage differences in the proportion of deviance explained (D^2) and area under the receiver operating characteristic (AUC) for the model ensemble mean relative to individual plant distribution models fitted using alternate climate datasets ($n = 8$) across all species ($n = 37$).

Table 5.3: Mean pairwise percentage differences in the proportion of deviance explained for plant distribution models fitted using discrete monthly mean (MM) or time-series (TS) climate datasets relative to ensemble means (μ) across all species ($n = 37$). Statistical comparisons performed using one-tailed pairwise t-tests with Holm-Bonferroni adjustment for multiple comparisons. Note that statistical differences do not always correspond to the magnitude of mean pairwise percentage differences due to dispersion in the results.

	WC1	WC2	VECD	VTCD	VTCD+M	VECD	VTCD	VTCD+M
	(MM) ¹	(MM) ²	(MM) ^{3,4}	(MM) ^{3,4}	(MM) ^{3,4}	(TS) ^{3,5}	(TS) ^{3,5}	(TS) ^{3,5}
μ WC	17.0***	7.8***	-0.3	1.4	3.0	2.5	2.0	0.7
μ VECD	23.3***	13.6**	5.1**	6.8**	8.6***	8.0***	7.5***	6.1*
μ VTCD	23.1***	13.5***	4.9*	6.7***	8.4***	7.8***	7.4***	6.0**
μ VTCD+M	22.9***	13.3***	4.8	6.5**	8.3***	7.7**	7.2***	5.8***
μ VIC (MM)	21.9***	12.4***	3.9***	5.7***	7.4***	6.8*	6.4*	5.0
μ VIC (TS)	19.9***	10.5*	2.2	3.9	5.6	5.0***	4.6***	3.2**
μ VIC (ALL)	27.2***	17.3***	8.4***	10.2***	12.0***	11.4***	11.0***	9.5***
μ ALL	29.2***	19.1***	10.1***	12.0***	13.8***	13.2***	12.7***	11.2***

¹ Hijmans et al. 2005; ² Fick & Hijmans 2017; ³ Stewart & Nitschke 2017/Chapter 2; ⁴ Fedrigo et al. 2019; ⁵ Chapter 4.

WC1 = WorldClim, WC2 = WorldClim v2; VECD = Victorian elevation-only climate dataset; VTCD = Victorian topo-climate dataset; VTCD+M = Victorian elevation plus MODIS climate dataset.

Statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

The statistical performance of ensemble means relative to individual models are summarised per species in Figure 5.4. The ensemble means performed better than any of the individual models for close to half of all species assessed ($n = 16$). The remaining species had at least 1 ($n = 13$) but no more than 3 ($n = 3$) separate models which performed better than the ensemble mean. There were no apparent trends in which of the climate datasets tended to work better than the ensembles, with each of the 8 datasets outperforming the ensemble mean at least once across all species.

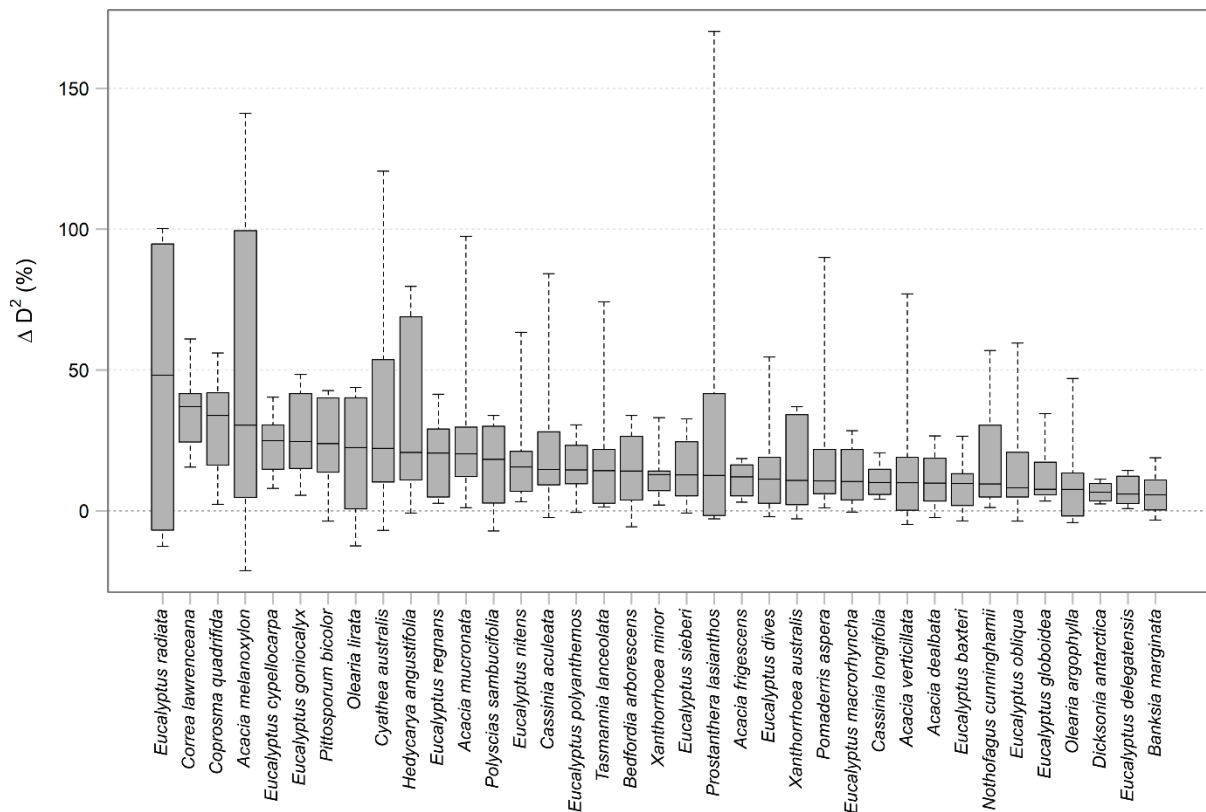


Figure 5.4: Percentage difference in the cross-validated proportion of deviance explained for the ensemble mean of species distribution models fitted using distinct climate datasets ($n = 8$) relative to individual models. Boxes correspond to interquartile range, whiskers to data extremes.

Spatial predictions for *Acacia melanoxylon* (Figure 5.5) were among the most variable when comparing individual models against the ensemble mean (Figure 5.4). Divergent predictions were frequent, even among climate datasets modelled using similar techniques. Highly variable predictions were common across each of the species assessed and were reflected in cross-validation statistics (e.g. Figure 5.4).

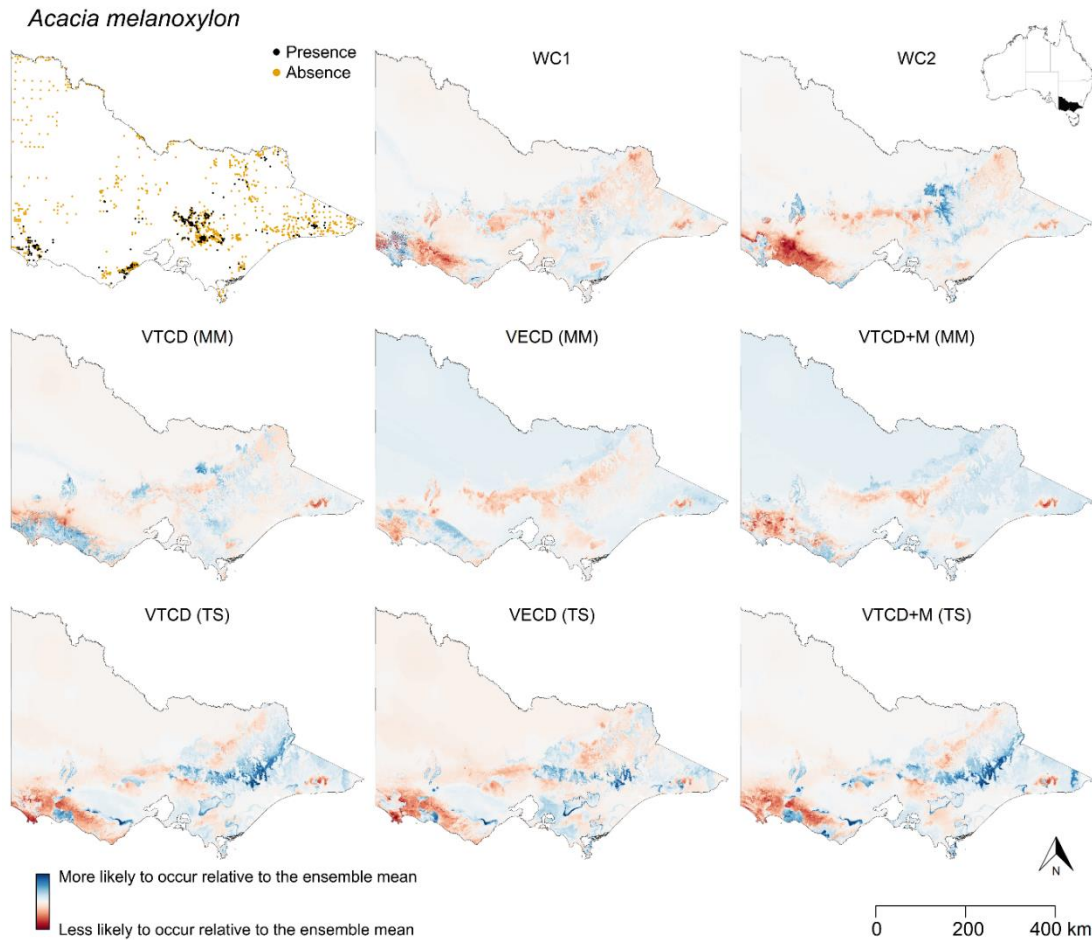


Figure 5.5: Difference in model predictions relative to the ensemble mean for *Acacia melanoxylon* across Victoria, southeast Australia.

The spatial congruence and uncertainty among individual model predictions for *Acacia melanoxylon*, *Eucalyptus radiata* and *Pomaderris aspera* as represented by the *TAI* and *TSD* are illustrated in Figure 5.6. The *TAI* indicates model congruence as it approaches -1 or 1, and highlights areas of potential disagreement where the ensemble mean falls near the optimal classification threshold. Regions close to the optimal threshold (i.e. $TAI \cong 0$) tend to occur around the edges of the predicted distribution and emphasise patterns which are not immediately clear with the individual models alone. The *TAI* acts like a binary classification but retains numerically continuous information on the level of congruence between competing models (Figure 5.7). The *TSD* provides a measure of uncertainty which is most sensitive to regions close to the optimal classification threshold. The standard deviation is penalised as the *STS* increases, and therefore acts to filter out regions with the highest level of congruence in modelled predictions (Figures 5.6 and 5.7). Maps of ensemble probabilities, *TAI* and *TSD* for each species are illustrated in Appendix 5.C.

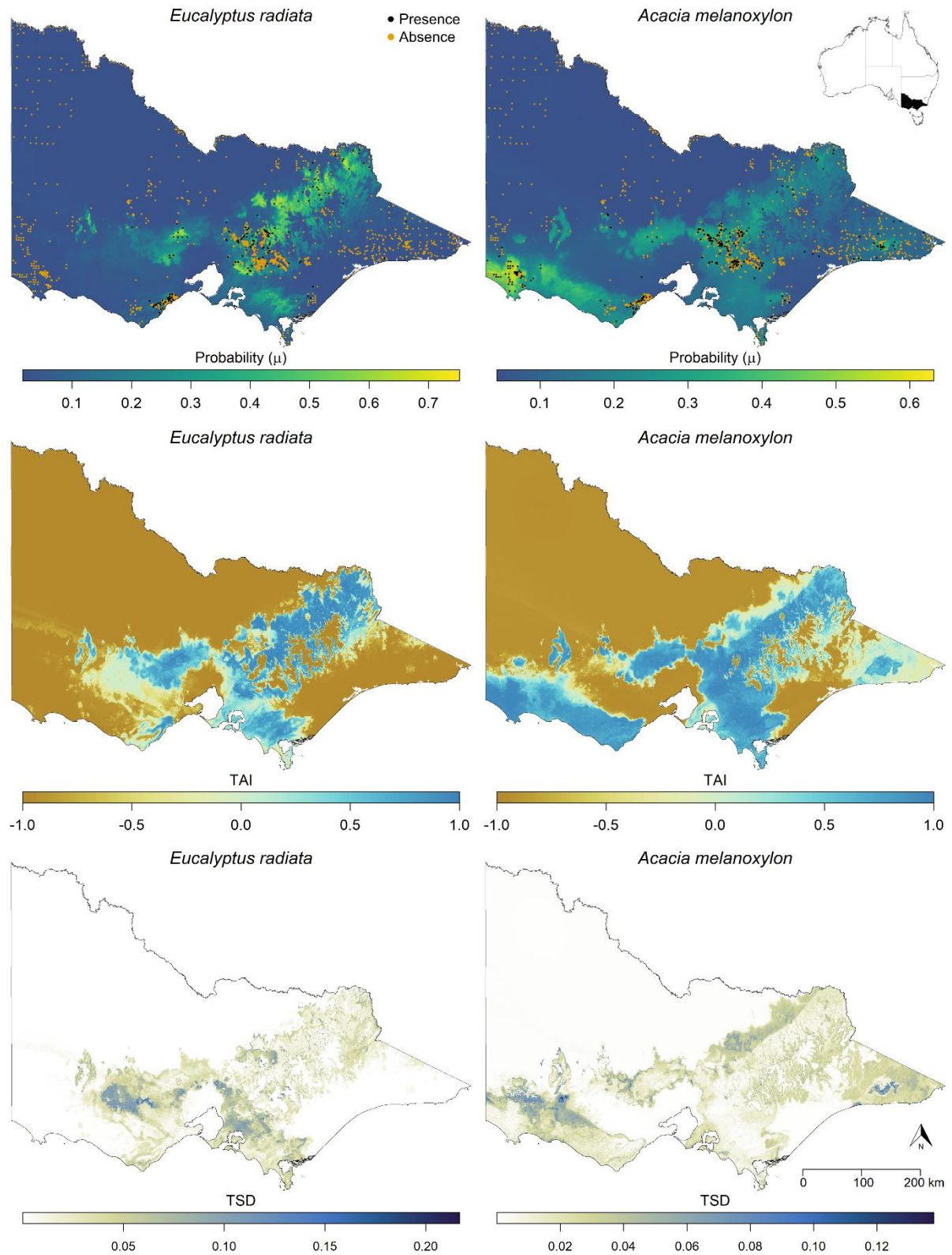


Figure 5.6: Spatial distribution of the threshold agreement index (*TAI*) and threshold-scaled standard deviation (*TSD*) for species distribution models fitted using 8 distinct sets of climate variables across Victoria, southeast Australia.

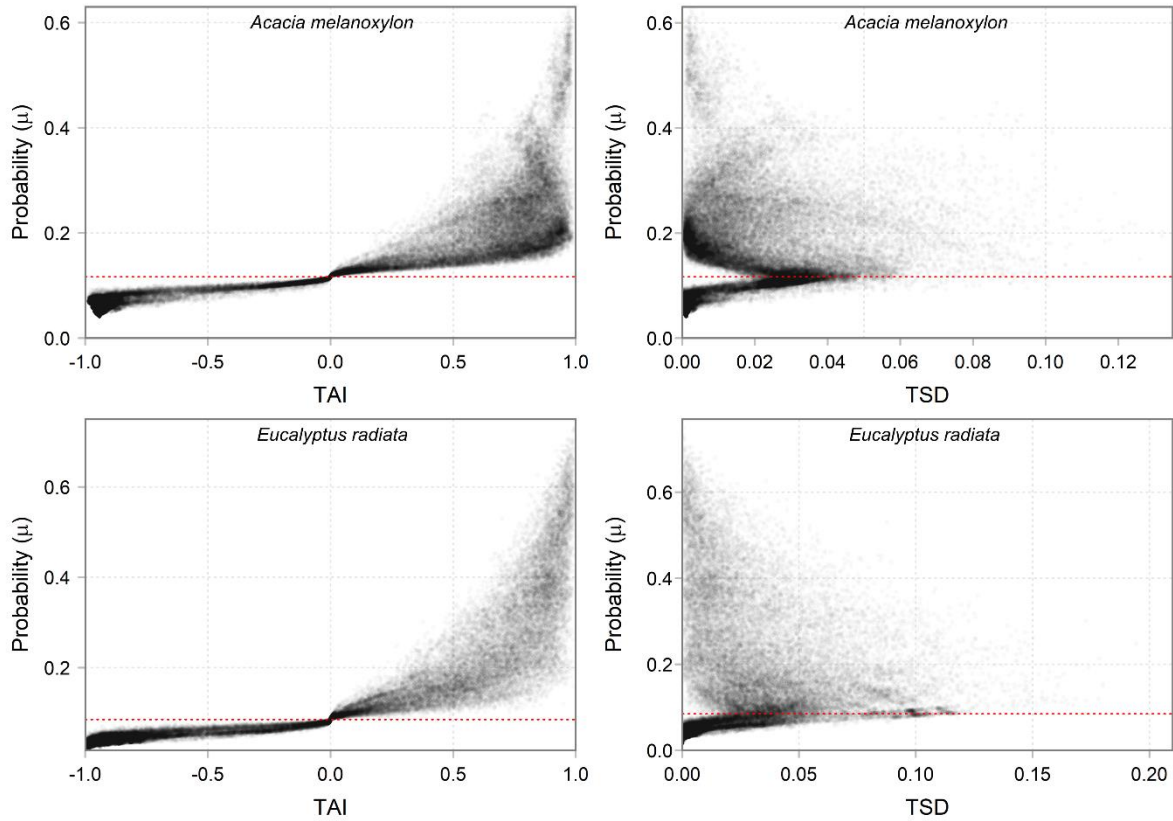


Figure 5.7: Scatterplot of the mean probability (μ) and threshold agreement index (TAI) for species distribution models fitted using 8 distinct sets of climate variables across Victoria, southeast Australia. Dotted red lines correspond to the threshold which maximises the cross-validated sum of sensitivity and specificity.

5.4. DISCUSSION

Relatively few studies have compared alternate climate datasets in species distribution modelling applications. Studies by Bedia et al. (2013), Soria-Auza et al. (2010) and Karger et al. (2017) have recommended specific datasets which best represent the physical processes occurring in a region based on the performance of species distribution models. While a better representation of local, fine-scale climatology can be achieved empirically (e.g. Karger et al. 2017) or with the support of remote sensing data (e.g. Stewart & Nitschke 2017/Chapter 2; Fick & Hijmans 2017), our results suggest that such improvements may not always benefit ecological models directly, at least not in a way that can be consistently achieved across species.

The regionally calibrated climate data (i.e. VECD, VTCD and VTCD+M) demonstrated performance improvements relative to the global WorldClim datasets, although this was only statistically significant for the original WorldClim dataset after correcting for multiple comparisons. The monthly mean VECD dataset was interpolated using near-identical methods to the original WorldClim study, and yet they showed the largest difference in mean performance relative to any other pairwise assessment. The primary differences between these datasets are their spatial resolution (approx. 250m vs 1 km), reference period (1981–2010 vs 1950–2000), weather station observations, and precipitation interpolation methodology. The regional precipitation data was interpolated on a smoothed DEM to account for the lack of strong correlation between elevation and precipitation at scales below 5-10 km (Hutchinson 1998; Sharples et al 2005; Stewart et al. 2017/Chapter 3). The differences in results between VECD and WorldClim are likely most driven by the different interpolation methodologies and input weather station observations, as the magnitude of difference in spatial grain and reference period were unlikely to significantly impact performance (e.g. Guisan et al. 2007; Morán-Ordóñez et al. 2016).

We expected regional datasets which were calibrated with the support of MODIS LST (VTCD+M) to considerably outperform those which only used topography (VECD; VTCD) during the interpolation procedure. The VTCD+M models did not perform any better than the simpler VECD models, despite up to 39% and 6% reduction in RMSE for minimum and maximum temperature interpolations, respectively, when supported with the use of MODIS LST (Stewart & Nitschke 2017/Chapter 2). Strong responses to minimum temperature were not common in the species assessed (Chapter 4), which could partially explain this result. Work by Deblauwe et al. (2017) on modelled plant species distributions across the tropics indicated that remotely sensed temperature (MODIS LST) and precipitation (CHIRPS; Funk et al. 2015) performed better than WorldClim. A direct comparison to these findings is not possible however as they used remote sensing data directly rather than as part of the interpolation process, used a null model for performance evaluation, and conducted their study in tropical climates as opposed to the climate of southeast Australia. Each of our regional datasets however demonstrated a performance improvement over the original WorldClim dataset, suggesting that the result cannot be attributed to the use of linear interpolation covariates such as MODIS LST.

The time-series derived variable sets did not show a significant improvement over the monthly mean models, despite representing inter-annual variability in extremes which had

previously shown better performance relative to extreme seasonality alone (Chapter 4). It is likely that the monthly mean surfaces are less prone to error accumulation as they are interpolated directly, as opposed to the extreme variables which are derived from a stacked series of 33 contributing years. Even though there was no strong trend in models using the regional climate datasets, there were clear additive performance improvements which could be achieved with ensembles.

Ensembles performed better than 89% of the individual models and provided the highest statistical performance for close to half of the species we assessed. Our results suggest that the use of ensembles can offset the risk of a poorly selected climate baseline and may outweigh the impact of potentially overlooking individual models with optimal statistical performance. This is supported by the fact that there were no clear trends in which dataset performed best for the small number of cases where individual models performed better than the ensemble. The variability of spatial predictions when using alternate contemporary climate datasets has previously been reported by Baker et al. (2016), and ensembles provide a mechanism to complement the strengths and weaknesses of different predictors.

One of the challenges in building effective multi-model ensembles is ensuring the contributing models maintain low bias and covariance relative to the variance of predictions (Dormann et al. 2018). These concepts are central to the widespread success of machine learning algorithms and ensemble techniques in climatology and finance. The presence of a bias in model predictions or spatial covariates may go undetected without ground truthing of environmental conditions (e.g. validation using weather stations in data sparse regions). An example of this phenomenon is precipitation in the Royal Himalayan Kingdom of Bhutan (located between India and the Tibetan plateau), which has been used as an example in several studies both with and without the use of local weather station observations. The original WorldClim (Hijmans et al. 2005) interpolations result in wet valleys with decreasing rainfall at higher elevations, whereas the empirical downscaling technique applied by Karger (et al. 2017) in the CHELSEA dataset results in a more realistic climatology, with dry valleys and rainfall increasing with elevation. Neither of these datasets make direct or indirect use of the local weather station network. The region is known for semi-arid valleys and ranges, and local interpolations indicate that while precipitation does tend to increase with elevation, it does not vary as strongly with topography (i.e. the predicted surface is much smoother) as indicated by either CHELSEA or WorldClim (Stewart et al. 2017/Chapter 3). Given the amount of

uncertainty in climatological data it may be most pragmatic to trade-off potential biases with ensembles rather than accept a singular point of truth.

The proposed *TAI* characterises congruence across any number of predictions at a specific location. Unlike the incongruence metrics applied by Morales-Barbero and Vega-Álvarez (2018), the *TAI* is computed directly from modelled probabilities rather than the input climate surfaces themselves. This means that it is not dependent upon variable importance and can be applied to machine learning models which are able to fit non-linear trends and complex interactions between variables. The *TAI* could in theory be applied in a wide range of analyses where potential niche overlap is of interest, such as the evaluation of climate change scenarios. Furthermore, the *TAI* is flexible as the optimal classification threshold could be computed using a range of different methods (e.g. favouring either sensitivity or specificity). When congruence is low or the ensemble prediction is close to the optimal classification threshold (i.e. $TAI \cong 0$), the standard deviation of the predictions is assigned the highest weight for calculating the *TSD*. The *TSD* can be interpreted as a spatial representation of those regions which potentially benefitted the most from the model ensemble, have the highest level of uncertainty, and which would also have been most at risk from an erroneous prediction if only a single model was ever evaluated. The spatial coherence of these proposed metrics, often around the periphery of the predicted distribution, strongly suggest that their use could be valuable for evaluating risk across competing management and climate change scenarios.

5.5. CONCLUSION

The results of this study demonstrate how the selection of a specific climate dataset for modelling species distributions may not necessarily lead to improved spatial predictions, even when the statistical performance or conceptual representation of the physical processes is better relative to alternatives. Bias may be unknowingly introduced into predicted species distributions by selecting a single source of climate data. While we did find evidence that regional datasets performed better than global ones, the improvements were not consistent across all species. Model ensembles improved performance relative to most individual models. Each of the candidate climate datasets are subject to their own strengths, weaknesses and biases, and by using ensembles these differences can be traded off against one another. The proposed congruence (*TAI*) and uncertainty (*TSD*) metrics provide spatially continuous

surfaces which complement the ensemble mean and aid in the interpretation of contributing model behaviour. These metrics characterise the level of agreement between separate models and indicate where uncertainty is greatest. While we focused specifically on 37 long-lived plant species in southeast Australia, the analysis of different taxonomic groups in a range of diverse climates and with a mixture of regional and global datasets may strengthen support for ensembles in species distribution modelling. A better understanding of how species distribution models can benefit from alternate climate datasets and multi-model ensembles may lead to more robust predictions of current distributions and how these might shift under alternate scenarios such as a changing climate.

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5.7. APPENDICES

APPENDIX 5.A: ALTERNATE PRECIPITATION DATASETS ACROSS VICTORIA, SOUTHEAST AUSTRALIA

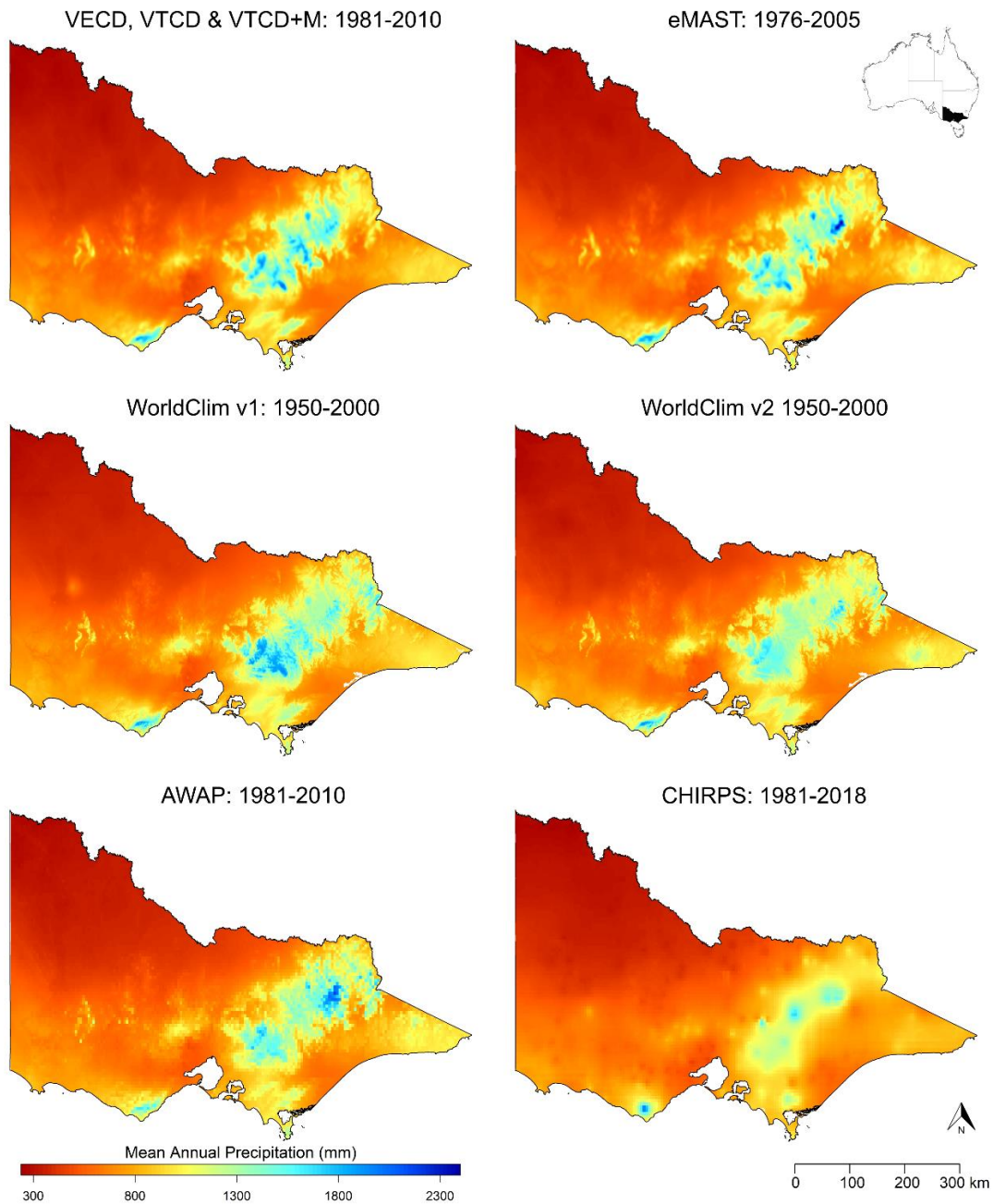


Figure 5.A.1: Gridded mean annual precipitation data across Victoria, southeast Australia, extracted from interpolations developed as part of Chapter 4 (VECD; VTCD and VTCD+M), the eMAST dataset (Xu et al. 2015), WorldClim (Hijmans et al. 2005; Fick & Hijmans 2017), the Australian Water Availability Project (Jones et al. 2009; Raupach et al. 2009; Raupach et al. 2012) and CHIRPS (Funk et al. 2015).

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APPENDIX 5.B: STATISTICAL PERFORMANCE OF SPECIES DISTRIBUTION MODELS FITTED USING ALTERNATE CLIMATE DATASETSTable 5.B.1: Cross-validated (spatially blocked k-fold) proportion of deviance explained (D^2) for distribution models fitted for 37 species using alternate climate monthly mean (MM) and time-series (TS) datasets ($n = 8$) in southeast Australia.

Species	P	A	k	VECD (MM) ^{1,2}	VTCD (MM) ^{1,2}	VTCD+M (MM) ^{1,2}	VECD (TS) ^{1,3}	VTCD (TS) ^{1,3}	VTCD+M (TS) ^{1,3}	WC1 (MM) ⁴	WC2 (MM) ⁵	μ (ALL)
<i>Acacia dealbata</i>	490	1316	6	0.19	0.17	0.21	0.21	0.19	0.22	0.17	0.20	0.22
<i>Acacia frigescens</i>	136	1670	5	0.17	0.18	0.16	0.19	0.18	0.17	0.19	0.16	0.19
<i>Acacia melanoxylon</i>	297	1509	6	0.04	0.07	0.04	0.09	0.11	0.09	0.07	0.05	0.09
<i>Acacia mucronata</i>	137	1669	5	0.19	0.17	0.16	0.15	0.16	0.16	0.10	0.17	0.20
<i>Acacia verticillata</i>	176	1630	5	0.16	0.19	0.16	0.17	0.20	0.19	0.11	0.17	0.19
<i>Banksia marginata</i>	210	1596	5	0.33	0.37	0.36	0.32	0.36	0.36	0.39	0.40	0.38
<i>Bedfordia arborescens</i>	183	1623	6	0.10	0.11	0.13	0.12	0.12	0.14	0.10	0.14	0.14
<i>Cassinia aculeata</i>	271	1535	6	0.17	0.16	0.14	0.18	0.16	0.15	0.14	0.10	0.18
<i>Cassinia longifolia</i>	177	1629	6	0.37	0.37	0.38	0.41	0.40	0.40	0.35	0.40	0.43
<i>Coprosma quadrifida</i>	445	1361	6	0.14	0.10	0.12	0.09	0.10	0.11	0.10	0.13	0.14
<i>Correa lawrenceana</i>	172	1634	4	0.20	0.17	0.17	0.15	0.17	0.18	0.19	0.21	0.24
<i>Cyathea australis</i>	222	1584	5	0.15	0.13	0.12	0.11	0.08	0.06	0.11	0.12	0.14
<i>Dicksonia antarctica</i>	406	1400	5	0.31	0.31	0.32	0.30	0.30	0.32	0.31	0.30	0.33
<i>Eucalyptus baxteri</i>	156	1650	5	0.23	0.25	0.26	0.21	0.23	0.24	0.23	0.27	0.26
<i>Eucalyptus cypellocarpa</i>	276	1530	6	0.20	0.19	0.20	0.20	0.21	0.23	0.22	0.18	0.25
<i>Eucalyptus delegatensis</i>	101	1705	4	0.41	0.42	0.43	0.40	0.38	0.42	0.38	0.38	0.43
<i>Eucalyptus dives</i>	164	1642	5	0.36	0.35	0.30	0.31	0.32	0.34	0.29	0.23	0.35
<i>Eucalyptus globoidea</i>	134	1672	5	0.44	0.48	0.48	0.47	0.48	0.49	0.38	0.43	0.51

Species	P	A	k	VECD (MM) ^{1,2}	VTCD (MM) ^{1,2}	VTCD+M (MM) ^{1,2}	VECD (TS) ^{1,3}	VTCD (TS) ^{1,3}	VTCD+M (TS) ^{1,3}	WC1 (MM) ⁴	WC2 (MM) ⁵	μ (ALL)
<i>Eucalyptus goniocalyx</i>	98	1708	5	0.32	0.25	0.27	0.34	0.31	0.26	0.30	0.24	0.36
<i>Eucalyptus macrorhyncha</i>	201	1605	5	0.39	0.41	0.42	0.43	0.45	0.46	0.36	0.36	0.46
<i>Eucalyptus nitens</i>	84	1722	4	0.24	0.24	0.23	0.21	0.22	0.22	0.21	0.15	0.25
<i>Eucalyptus obliqua</i>	459	1347	5	0.21	0.18	0.18	0.19	0.18	0.19	0.12	0.15	0.20
<i>Eucalyptus polyanthemus</i>	153	1653	5	0.34	0.32	0.31	0.35	0.34	0.38	0.30	0.29	0.38
<i>Eucalyptus radiata</i>	187	1619	5	0.18	0.17	0.17	0.08	0.08	0.08	0.09	0.13	0.16
<i>Eucalyptus regnans</i>	372	1434	4	0.53	0.48	0.52	0.42	0.42	0.42	0.38	0.52	0.54
<i>Eucalyptus sieberi</i>	147	1659	5	0.30	0.27	0.28	0.33	0.32	0.31	0.25	0.26	0.33
<i>Hedycarya angustifolia</i>	136	1670	5	0.08	0.08	0.07	0.05	0.05	0.05	0.07	0.07	0.08
<i>Nothofagus cunninghamii</i>	166	1640	4	0.48	0.45	0.46	0.51	0.48	0.49	0.35	0.33	0.51
<i>Olearia argophylla</i>	309	1497	5	0.20	0.20	0.19	0.17	0.18	0.16	0.13	0.18	0.19
<i>Olearia lirata</i>	215	1591	6	0.14	0.15	0.13	0.10	0.10	0.09	0.12	0.10	0.14
<i>Pittosporum bicolor</i>	110	1696	4	0.14	0.14	0.14	0.17	0.17	0.18	0.16	0.21	0.20
<i>Polyscias sambucifolia</i>	273	1533	5	0.16	0.17	0.17	0.24	0.21	0.20	0.17	0.21	0.22
<i>Pomaderris aspera</i>	333	1473	6	0.14	0.17	0.17	0.16	0.16	0.18	0.10	0.17	0.18
<i>Prostanthera lasianthos</i>	118	1688	4	0.18	0.13	0.12	0.18	0.18	0.16	0.07	0.16	0.18
<i>Tasmannia lanceolata</i>	121	1685	4	0.15	0.17	0.18	0.15	0.16	0.18	0.11	0.18	0.19
<i>Xanthorrhoea australis</i>	126	1680	4	0.29	0.29	0.21	0.25	0.25	0.27	0.21	0.21	0.28
<i>Xanthorrhoea minor</i>	152	1654	5	0.18	0.18	0.17	0.18	0.19	0.15	0.18	0.20	0.20

¹ Stewart & Nitschke 2017/Chapter 2; ² Fedrigo et al. 2019; ³ Chapter 4; ⁴ Hijmans et al. 2005; ⁵ Fick & Hijmans 2017.

P = presence; A = absence; k = number of block cross-validation folds; VECD = Victorian elevation-only climate dataset; VTCD = Victorian topo-climate dataset; VTCD+M = Victorian elevation plus MODIS climate dataset; WC1 = WorldClim, WC2 = WorldClim v2; μ = ensemble mean of predictions from each climate dataset.

Table 5.B.2: Cross-validated (spatially blocked k-fold) area under the receiver operating characteristic (*AUC*) for distribution models fitted for 37 species using alternate monthly mean (MM) and time-series (TS) climate datasets ($n = 8$) in southeast Australia.

Species	P	A	k	VECD (MM) ^{1,2}	VTCD (MM) ^{1,2}	VTCD+M (MM) ^{1,2}	VECD (TS) ^{1,3}	VTCD (TS) ^{1,3}	VTCD+M (TS) ^{1,3}	WC1 (MM) ⁴	WC2 (MM) ⁵	μ (ALL)
<i>Acacia dealbata</i>	490	1316	6	0.80	0.78	0.81	0.81	0.80	0.82	0.78	0.80	0.81
<i>Acacia frigescens</i>	136	1670	5	0.81	0.80	0.80	0.81	0.80	0.80	0.80	0.81	0.81
<i>Acacia melanoxylon</i>	297	1509	6	0.66	0.68	0.64	0.73	0.74	0.72	0.68	0.66	0.72
<i>Acacia mucronata</i>	137	1669	5	0.82	0.81	0.82	0.77	0.76	0.77	0.78	0.79	0.82
<i>Acacia verticillata</i>	176	1630	5	0.83	0.84	0.83	0.83	0.84	0.84	0.77	0.83	0.84
<i>Banksia marginata</i>	210	1596	5	0.90	0.91	0.91	0.90	0.90	0.91	0.93	0.92	0.92
<i>Bedfordia arborescens</i>	183	1623	6	0.79	0.79	0.80	0.79	0.78	0.80	0.79	0.79	0.80
<i>Cassinia aculeata</i>	271	1535	6	0.79	0.79	0.78	0.80	0.79	0.78	0.77	0.75	0.80
<i>Cassinia longifolia</i>	177	1629	6	0.89	0.89	0.90	0.91	0.91	0.91	0.89	0.92	0.91
<i>Coprosma quadrifida</i>	445	1361	6	0.76	0.74	0.75	0.75	0.76	0.76	0.73	0.77	0.76
<i>Correa lawrenceana</i>	172	1634	4	0.85	0.85	0.85	0.85	0.85	0.85	0.84	0.86	0.87
<i>Cyathea australis</i>	222	1584	5	0.79	0.77	0.77	0.77	0.76	0.76	0.76	0.79	0.78
<i>Dicksonia antarctica</i>	406	1400	5	0.87	0.87	0.87	0.87	0.87	0.88	0.87	0.86	0.88
<i>Eucalyptus baxteri</i>	156	1650	5	0.81	0.83	0.84	0.82	0.82	0.83	0.83	0.85	0.84
<i>Eucalyptus cypellocarpa</i>	276	1530	6	0.80	0.80	0.78	0.81	0.81	0.81	0.80	0.78	0.83
<i>Eucalyptus delegatensis</i>	101	1705	4	0.93	0.93	0.94	0.92	0.93	0.93	0.93	0.92	0.94
<i>Eucalyptus dives</i>	164	1642	5	0.90	0.89	0.86	0.87	0.88	0.89	0.88	0.85	0.90
<i>Eucalyptus globoidea</i>	134	1672	5	0.93	0.94	0.94	0.95	0.95	0.95	0.91	0.94	0.96
<i>Eucalyptus goniacalyx</i>	98	1708	5	0.92	0.90	0.89	0.92	0.91	0.87	0.89	0.88	0.93

Species	P	A	k	VECD (MM) ^{1,2}	VTCD (MM) ^{1,2}	VTCD+M (MM) ^{1,2}	VECD (TS) ^{1,3}	VTCD (TS) ^{1,3}	VTCD+M (TS) ^{1,3}	WC1 (MM) ⁴	WC2 (MM) ⁵	μ (ALL)
<i>Eucalyptus macrorhyncha</i>	201	1605	5	0.92	0.93	0.93	0.93	0.94	0.94	0.92	0.90	0.94
<i>Eucalyptus nitens</i>	84	1722	4	0.84	0.84	0.81	0.82	0.84	0.83	0.84	0.80	0.85
<i>Eucalyptus obliqua</i>	459	1347	5	0.81	0.80	0.80	0.80	0.80	0.80	0.74	0.78	0.81
<i>Eucalyptus polyanthemos</i>	153	1653	5	0.92	0.92	0.92	0.92	0.92	0.93	0.90	0.90	0.93
<i>Eucalyptus radiata</i>	187	1619	5	0.82	0.82	0.81	0.76	0.77	0.76	0.79	0.78	0.81
<i>Eucalyptus regnans</i>	372	1434	4	0.95	0.94	0.95	0.94	0.95	0.95	0.93	0.95	0.96
<i>Eucalyptus sieberi</i>	147	1659	5	0.83	0.82	0.82	0.86	0.86	0.86	0.83	0.83	0.86
<i>Hedycarya angustifolia</i>	136	1670	5	0.73	0.75	0.75	0.69	0.72	0.71	0.72	0.72	0.75
<i>Nothofagus cunninghamii</i>	166	1640	4	0.94	0.94	0.94	0.95	0.95	0.95	0.92	0.92	0.95
<i>Olearia argophylla</i>	309	1497	5	0.82	0.82	0.82	0.81	0.81	0.82	0.79	0.81	0.82
<i>Olearia lirata</i>	215	1591	6	0.77	0.77	0.74	0.74	0.73	0.72	0.74	0.72	0.75
<i>Pittosporum bicolor</i>	110	1696	4	0.82	0.82	0.81	0.84	0.84	0.85	0.83	0.85	0.85
<i>Polyscias sambucifolia</i>	273	1533	5	0.80	0.80	0.80	0.83	0.82	0.82	0.80	0.82	0.82
<i>Pomaderris aspera</i>	333	1473	6	0.78	0.79	0.80	0.81	0.81	0.82	0.75	0.80	0.81
<i>Prostanthera lasianthos</i>	118	1688	4	0.80	0.78	0.78	0.78	0.79	0.78	0.72	0.80	0.80
<i>Tasmania lanceolata</i>	121	1685	4	0.79	0.80	0.81	0.77	0.80	0.81	0.72	0.81	0.81
<i>Xanthorrhoea australis</i>	126	1680	4	0.87	0.87	0.85	0.87	0.86	0.86	0.85	0.85	0.87
<i>Xanthorrhoea minor</i>	152	1654	5	0.84	0.83	0.84	0.83	0.82	0.81	0.85	0.83	0.84

¹ Stewart & Nitschke 2017/Chapter 2; ² Fedrigo et al. 2019; ³ Chapter 4; ⁴ Hijmans et al. 2005; ⁵ Fick & Hijmans 2017.

P = presence; A = absence; k = number of block cross-validation folds; VECD = Victorian elevation-only climate dataset; VTCD = Victorian topo-climate dataset; VTCD+M = Victorian elevation plus MODIS climate dataset; WC1 = WorldClim, WC2 = WorldClim v2; μ = ensemble mean of predictions from each climate dataset.

APPENDIX 5.C: SPATIAL DISTRIBUTION OF SPECIES DISTRIBUTION MODEL

ENSEMBLES AND SUPPORTING METRICS

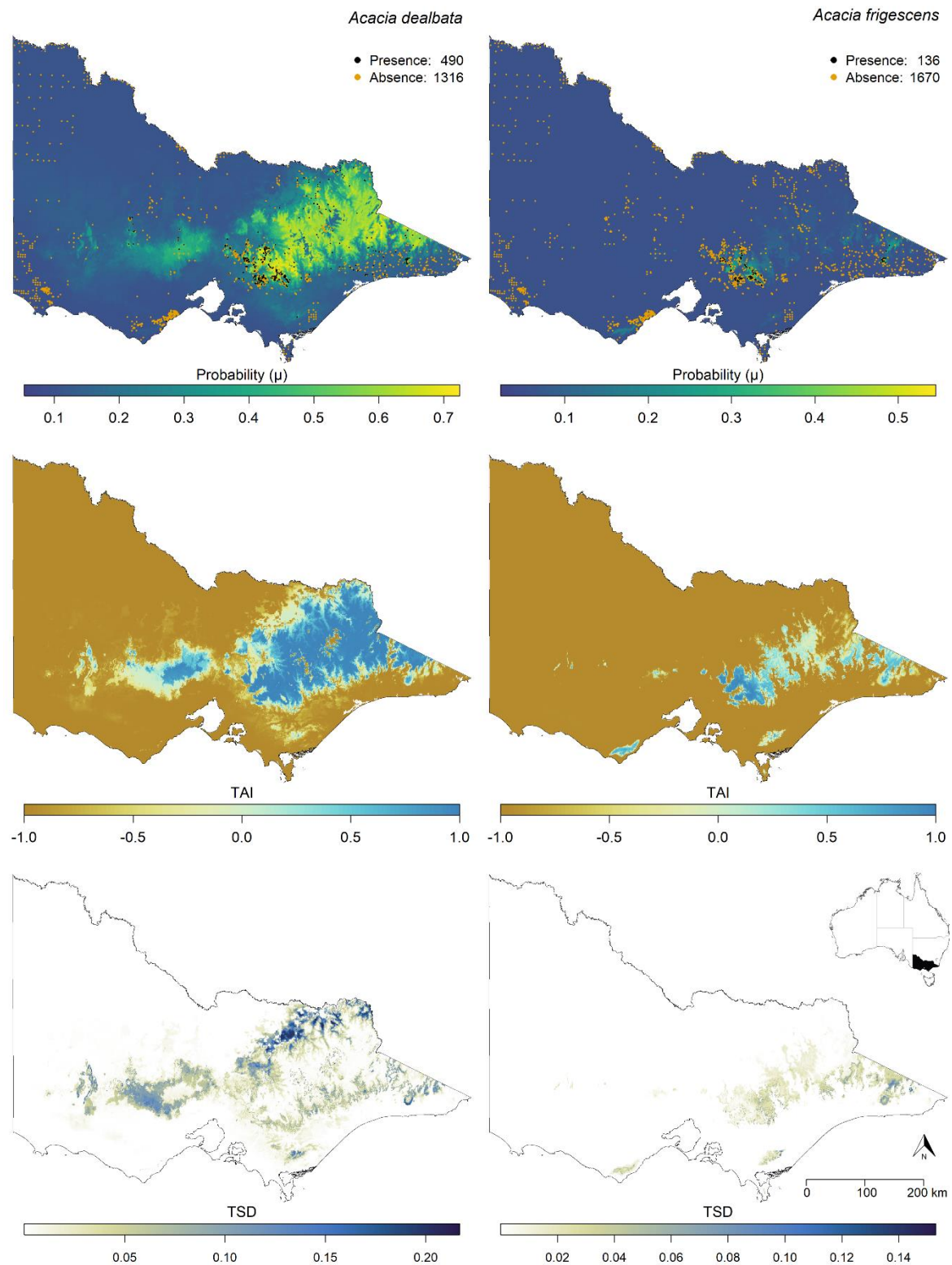


Figure 5.C.1: Spatial distribution of the ensemble mean probability (μ ; $n = 8$ models), threshold agreement index (TAI) and threshold-scaled standard deviation (TSD) for predictions of 37 tree species distributions in Victoria, southeast Australia.

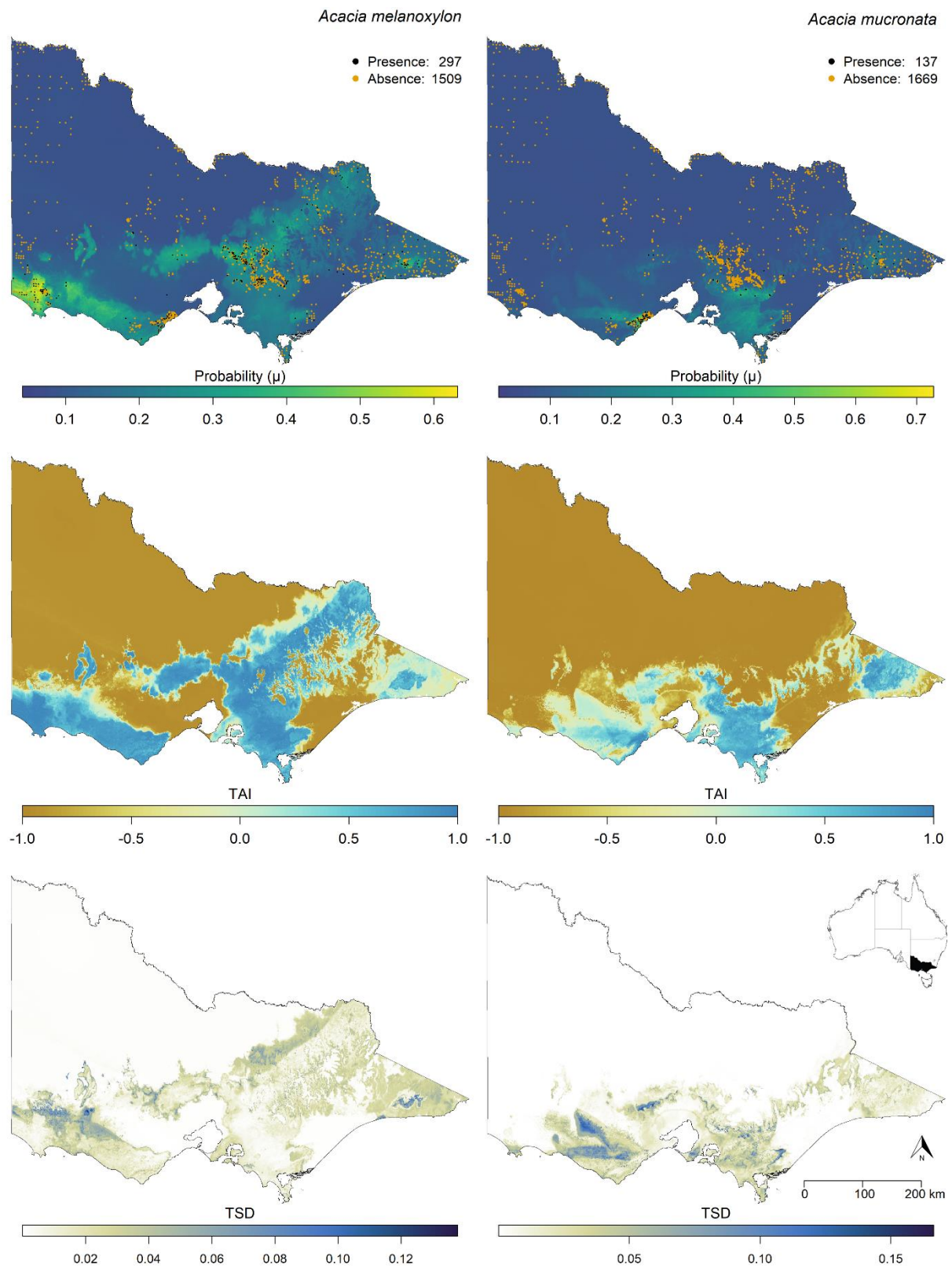


Figure 5.C.1: Continued.

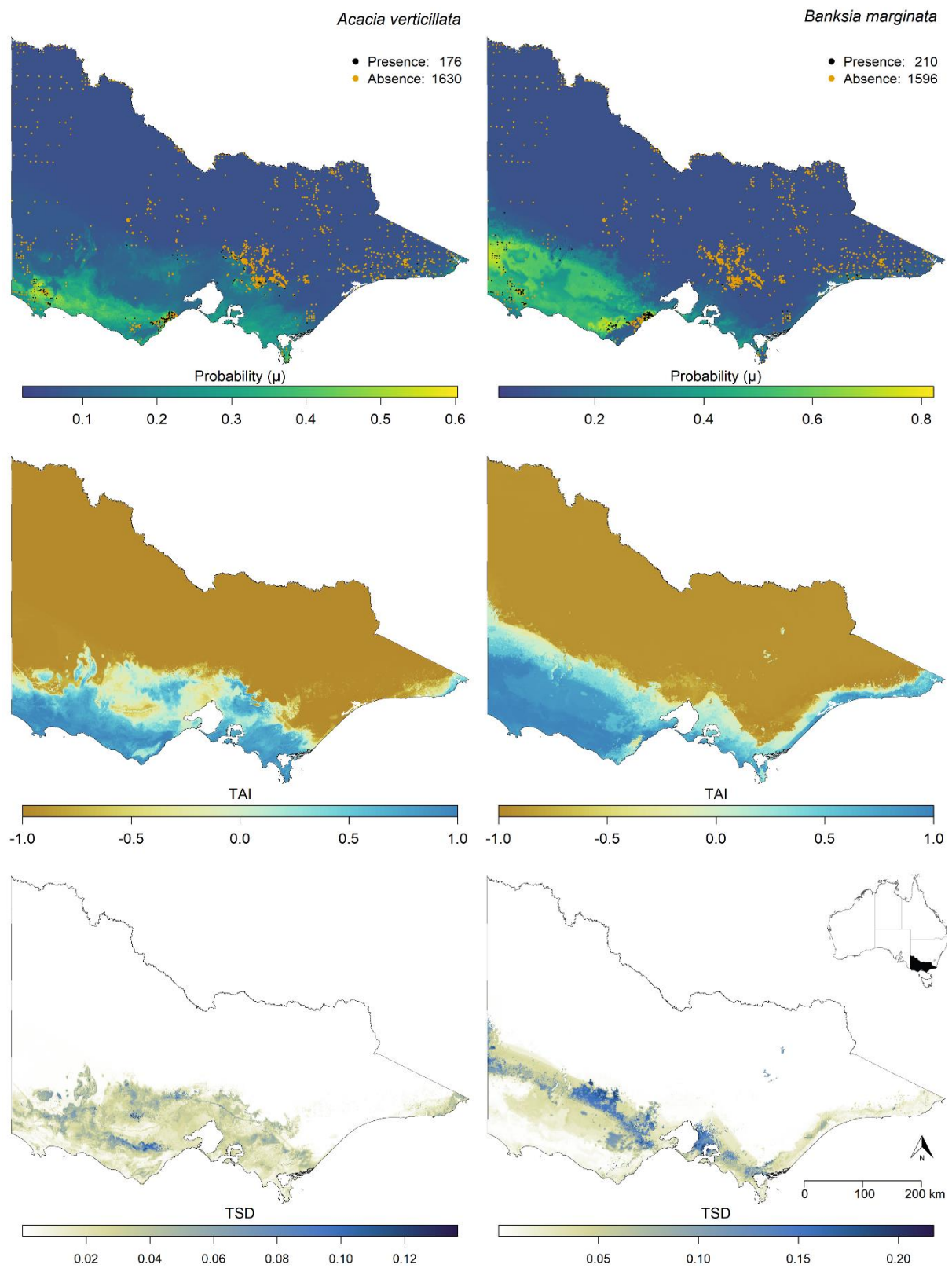


Figure 5.C.1: Continued.

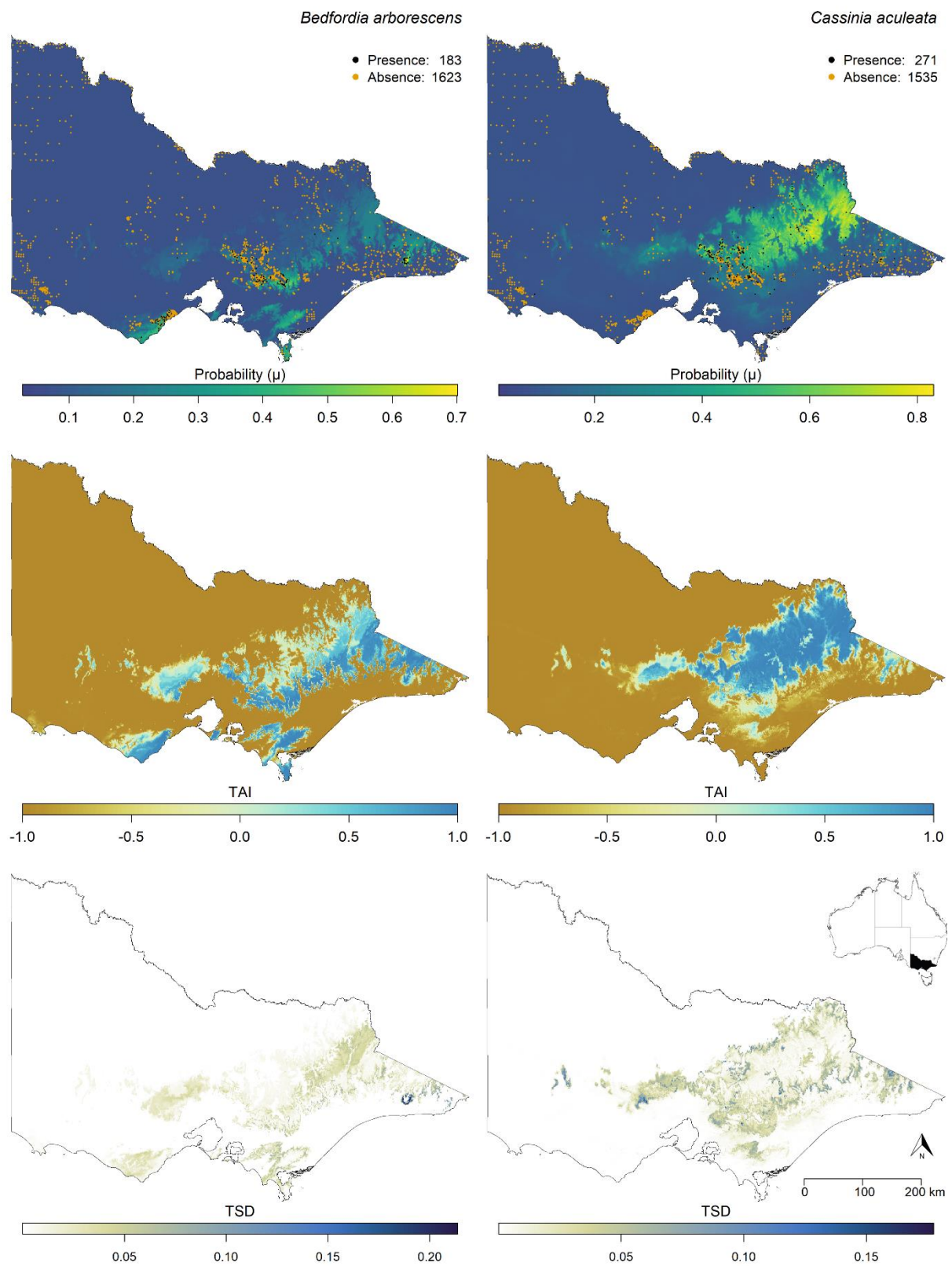


Figure 5.C.1: Continued.

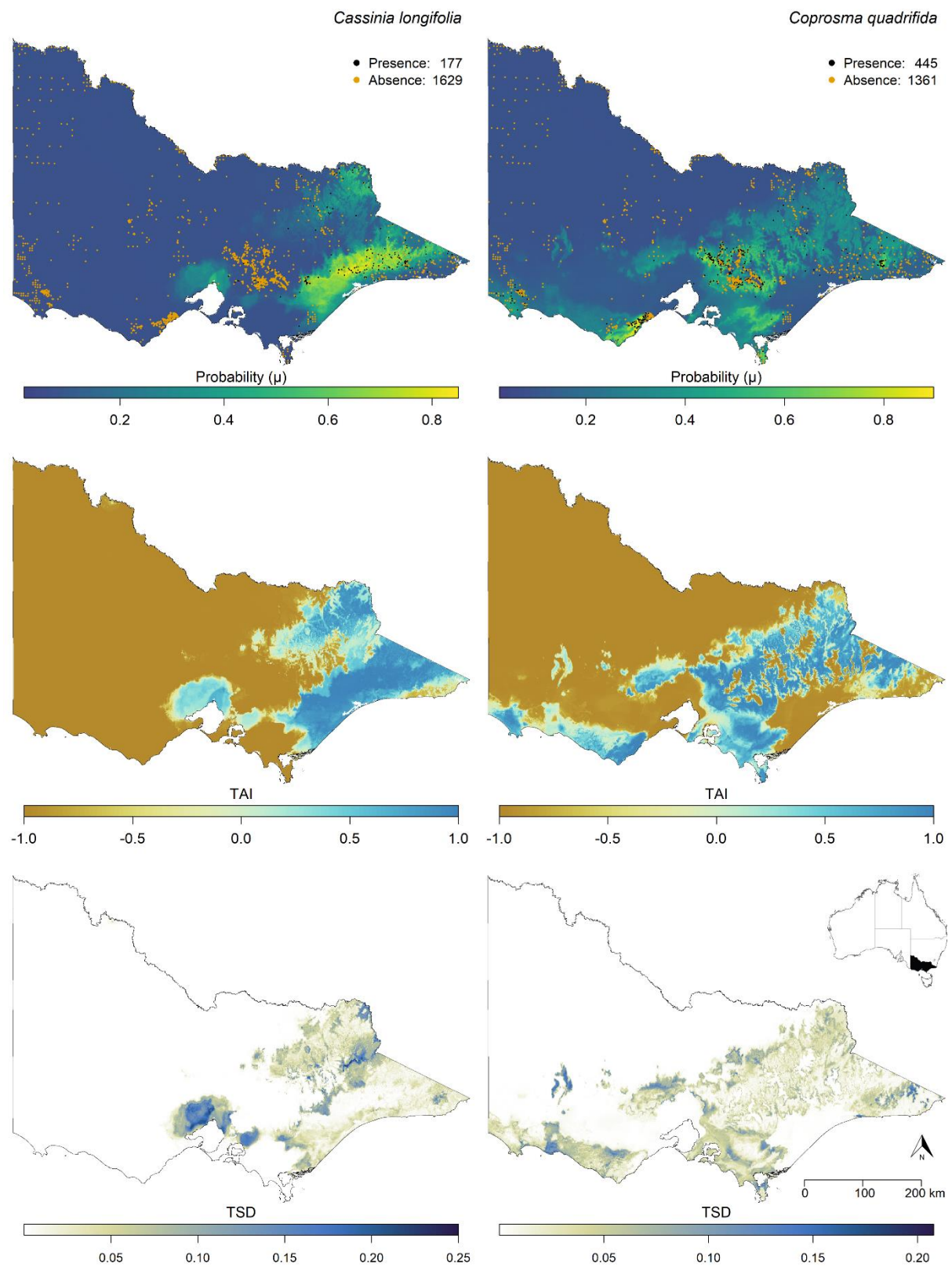


Figure 5.C.1: Continued.

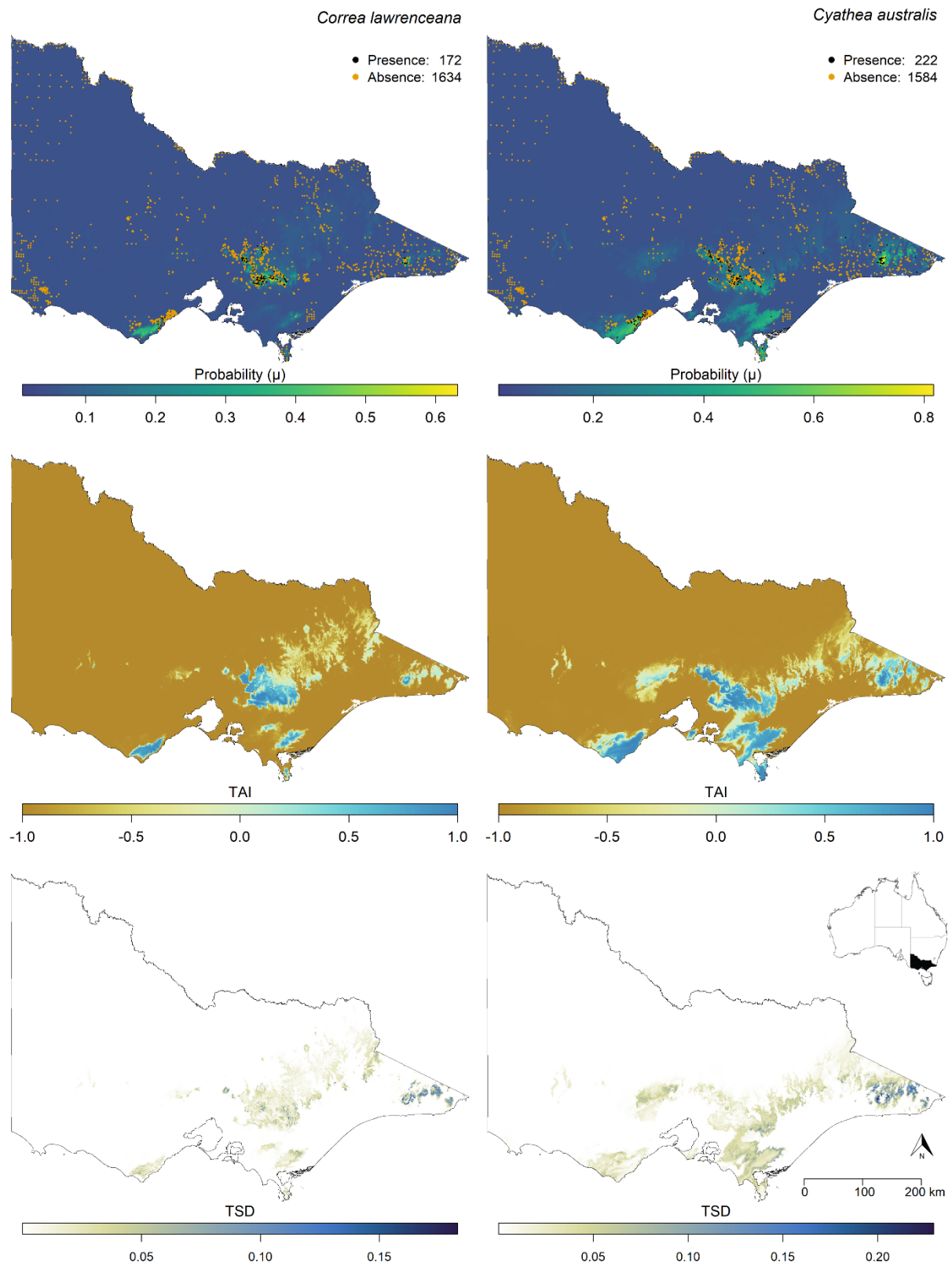


Figure 5.C.1: Continued.

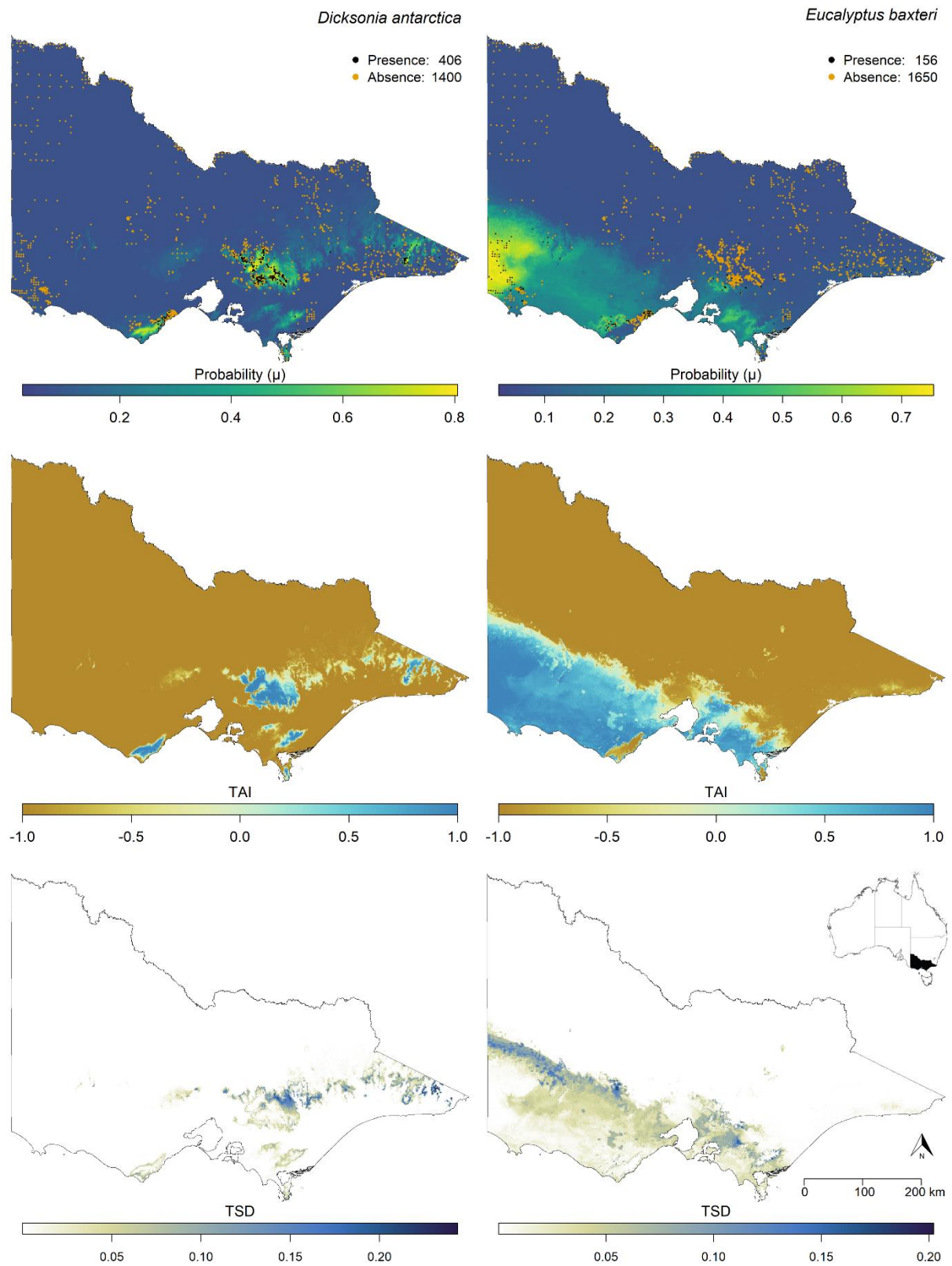


Figure 5.C.1: Continued.

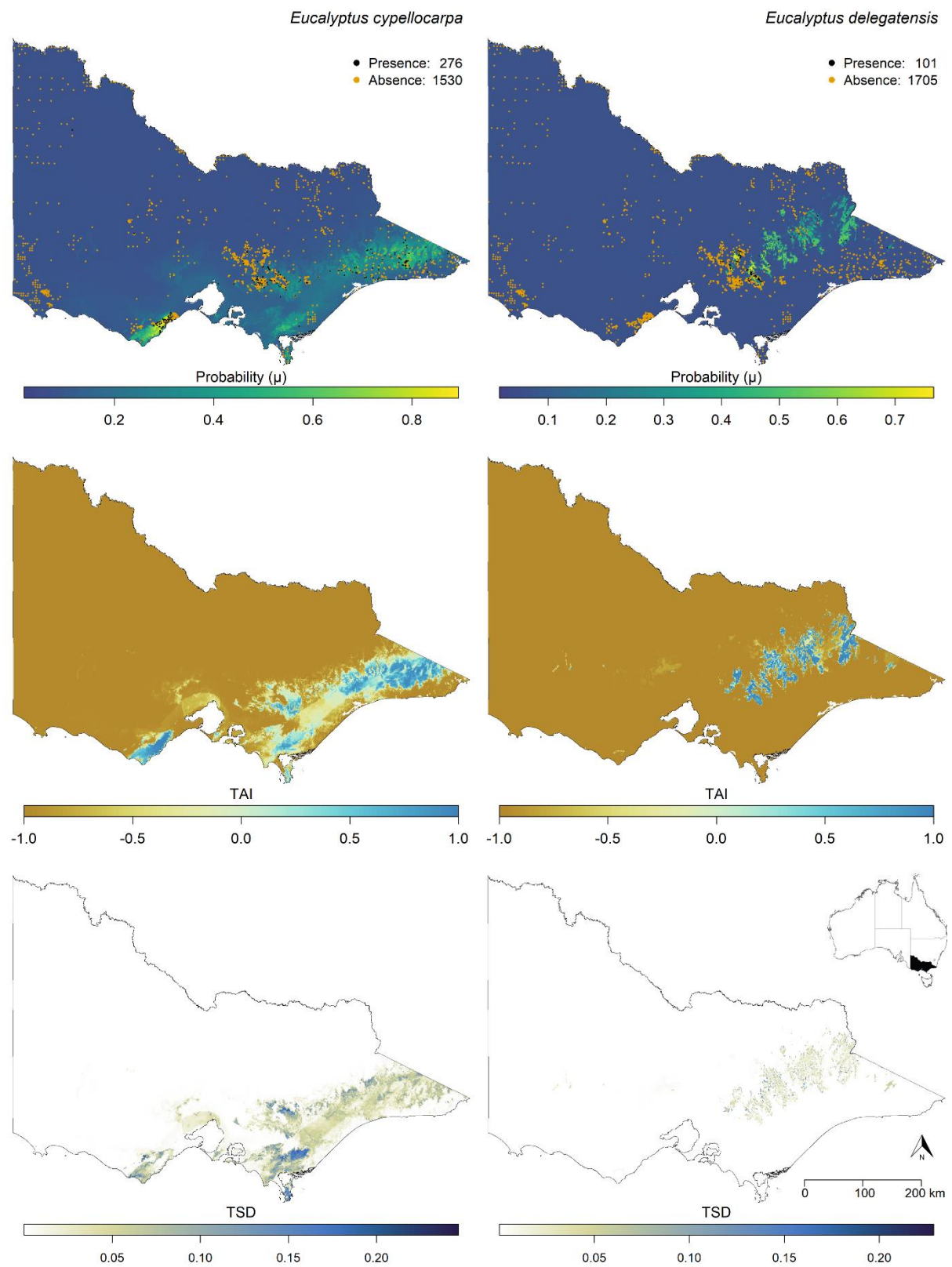


Figure 5.C.1: Continued.

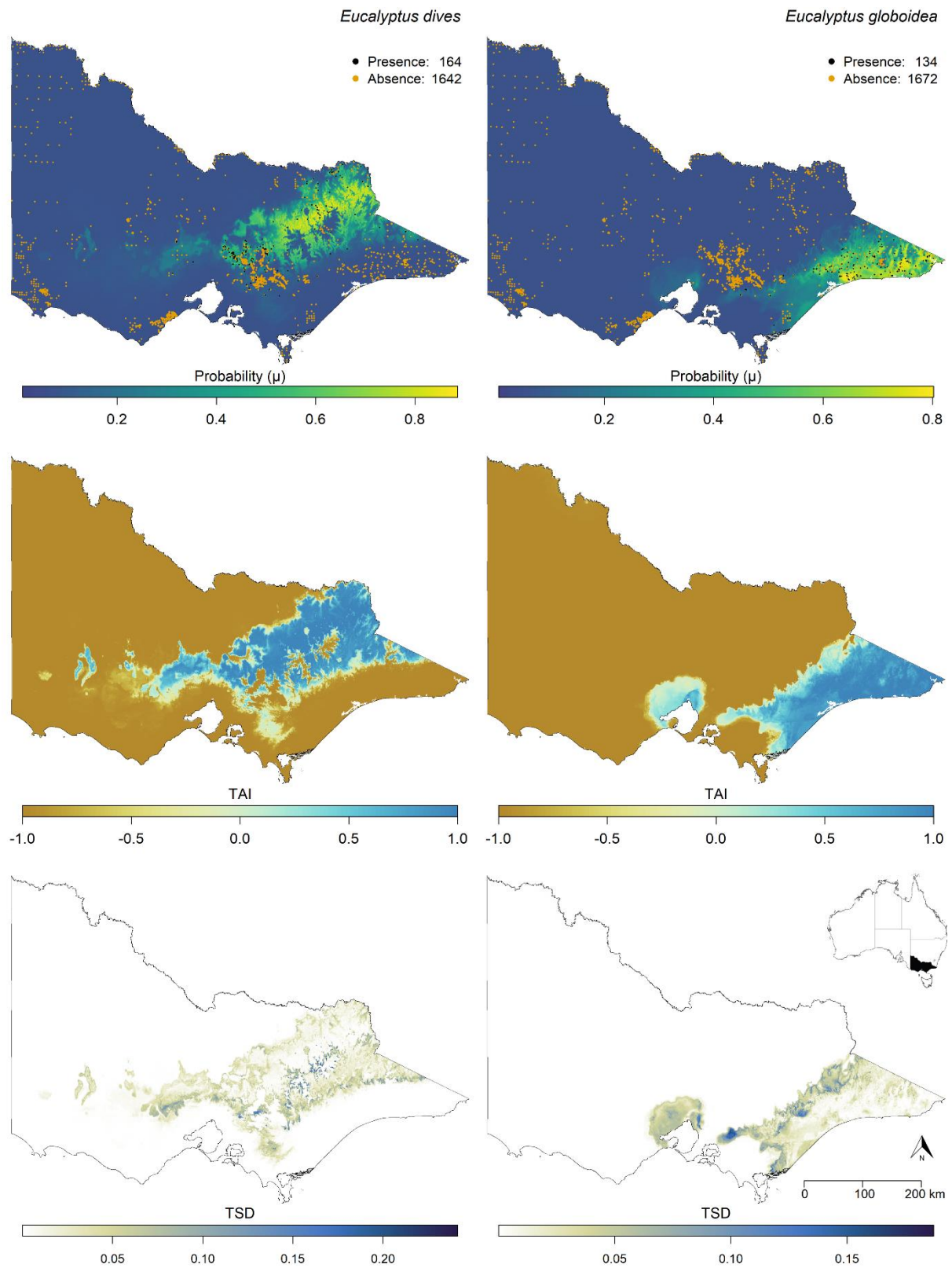


Figure 5.C.1: Continued.

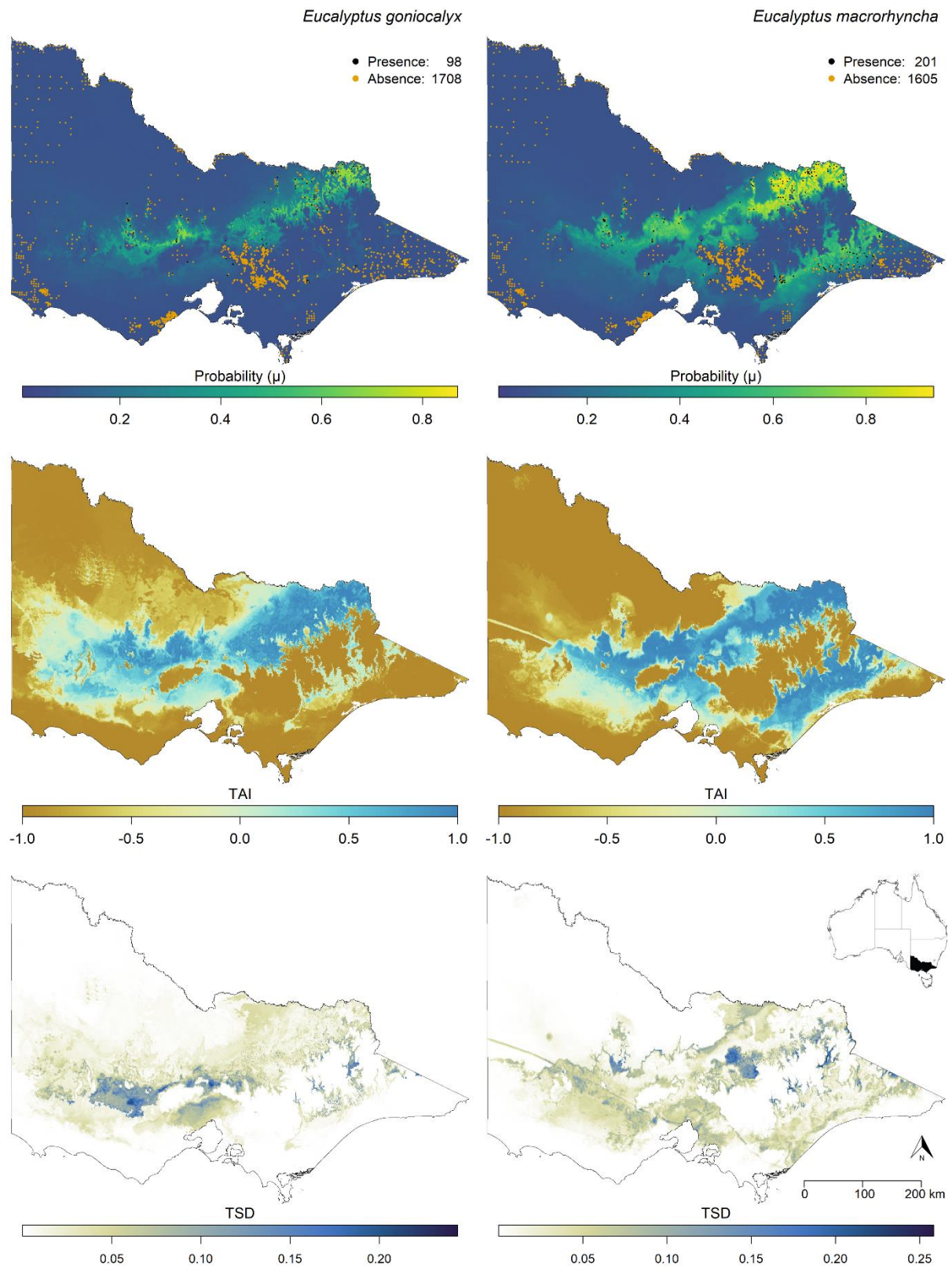


Figure 5.C.1: Continued.

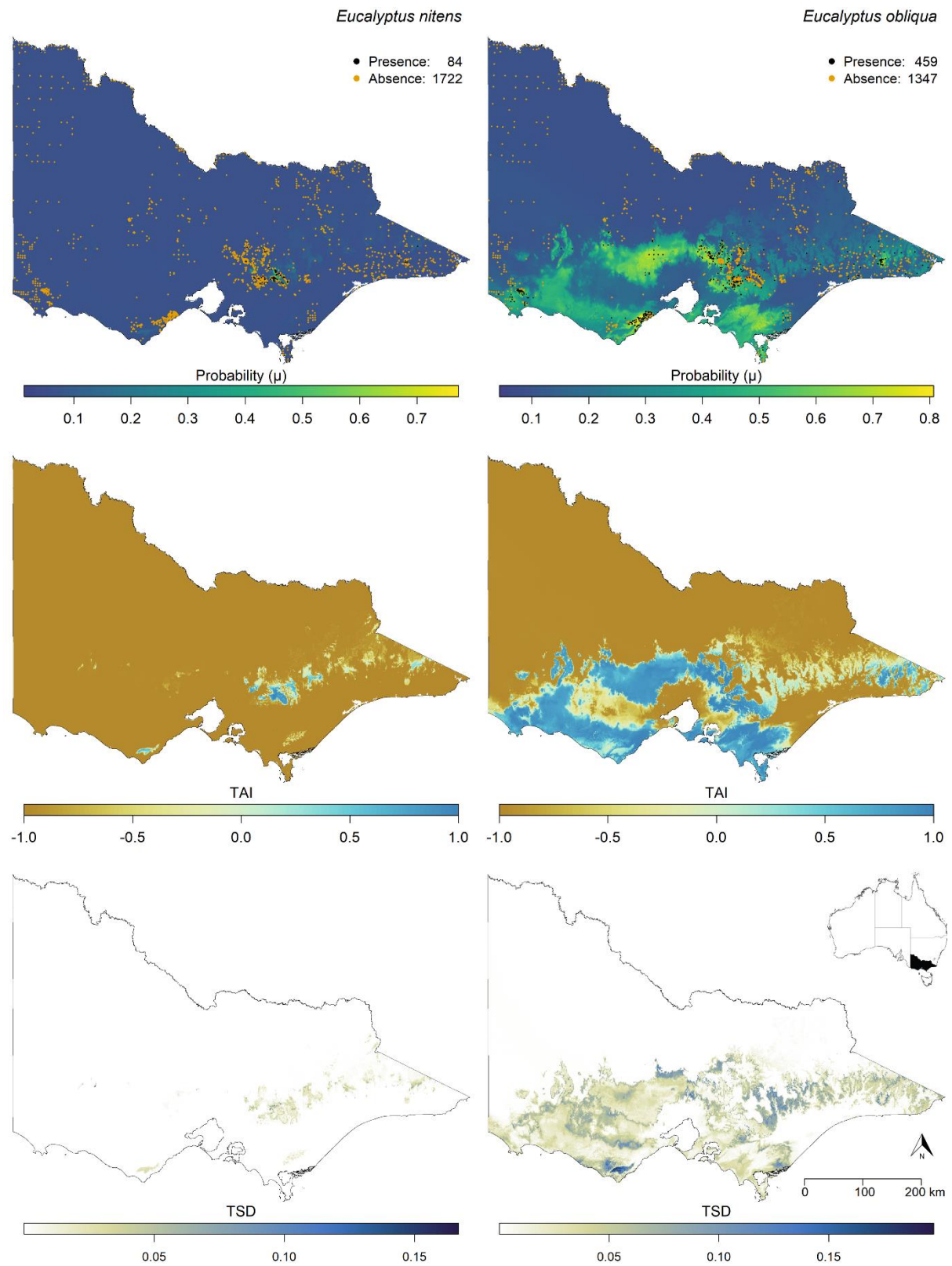


Figure 5.C.1: Continued.

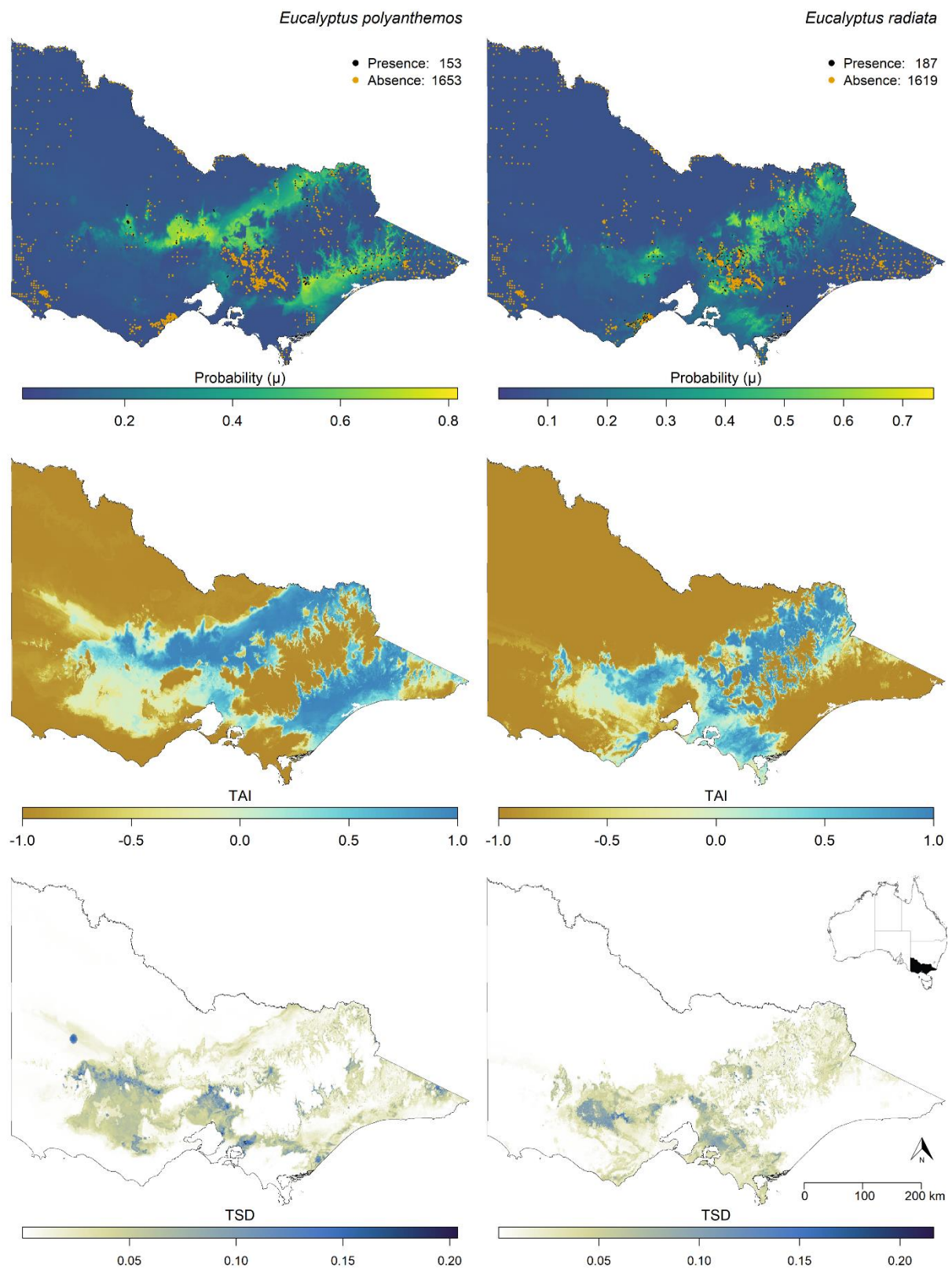


Figure 5.C.1: Continued.

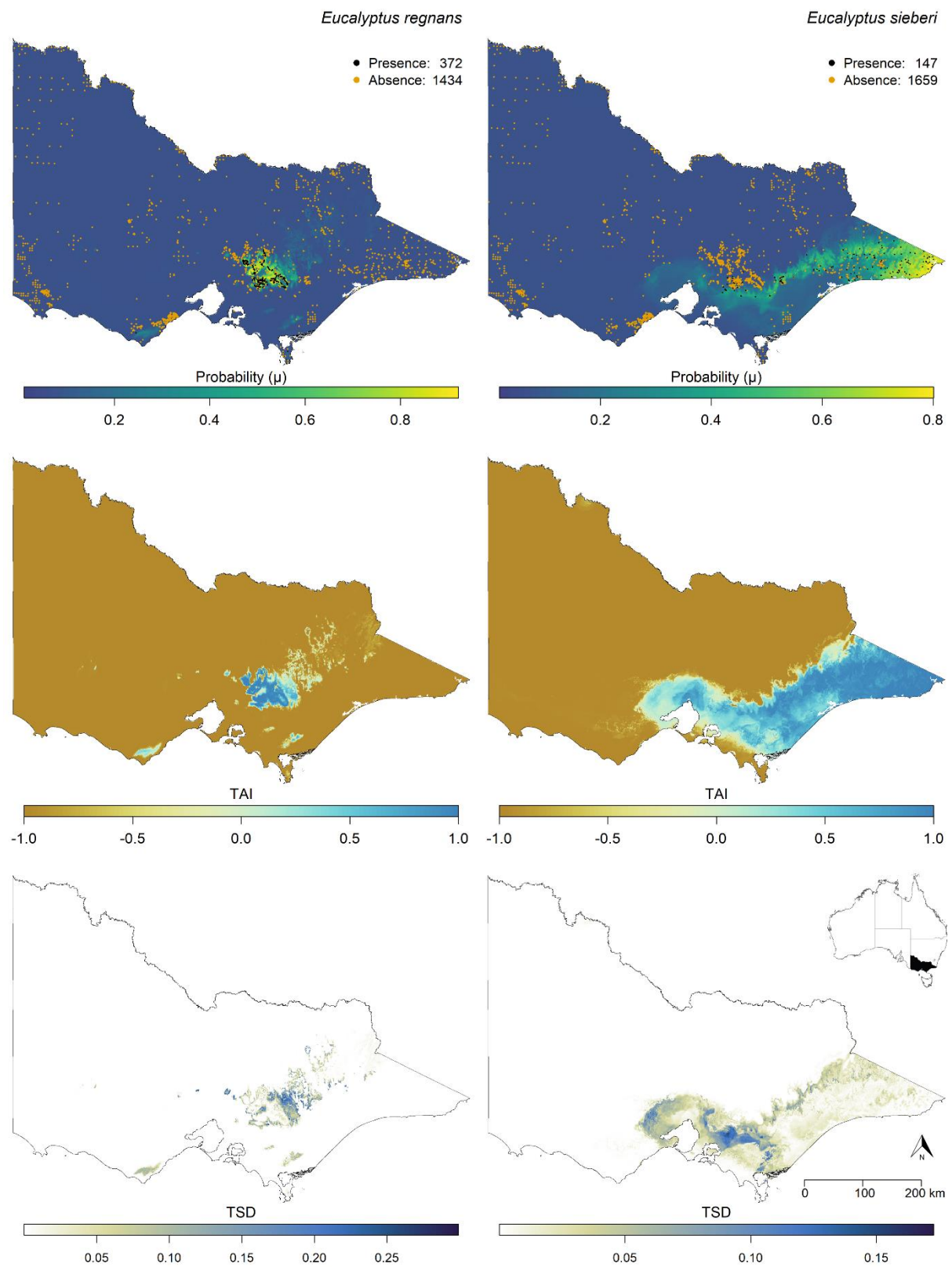


Figure 5.C.1: Continued.

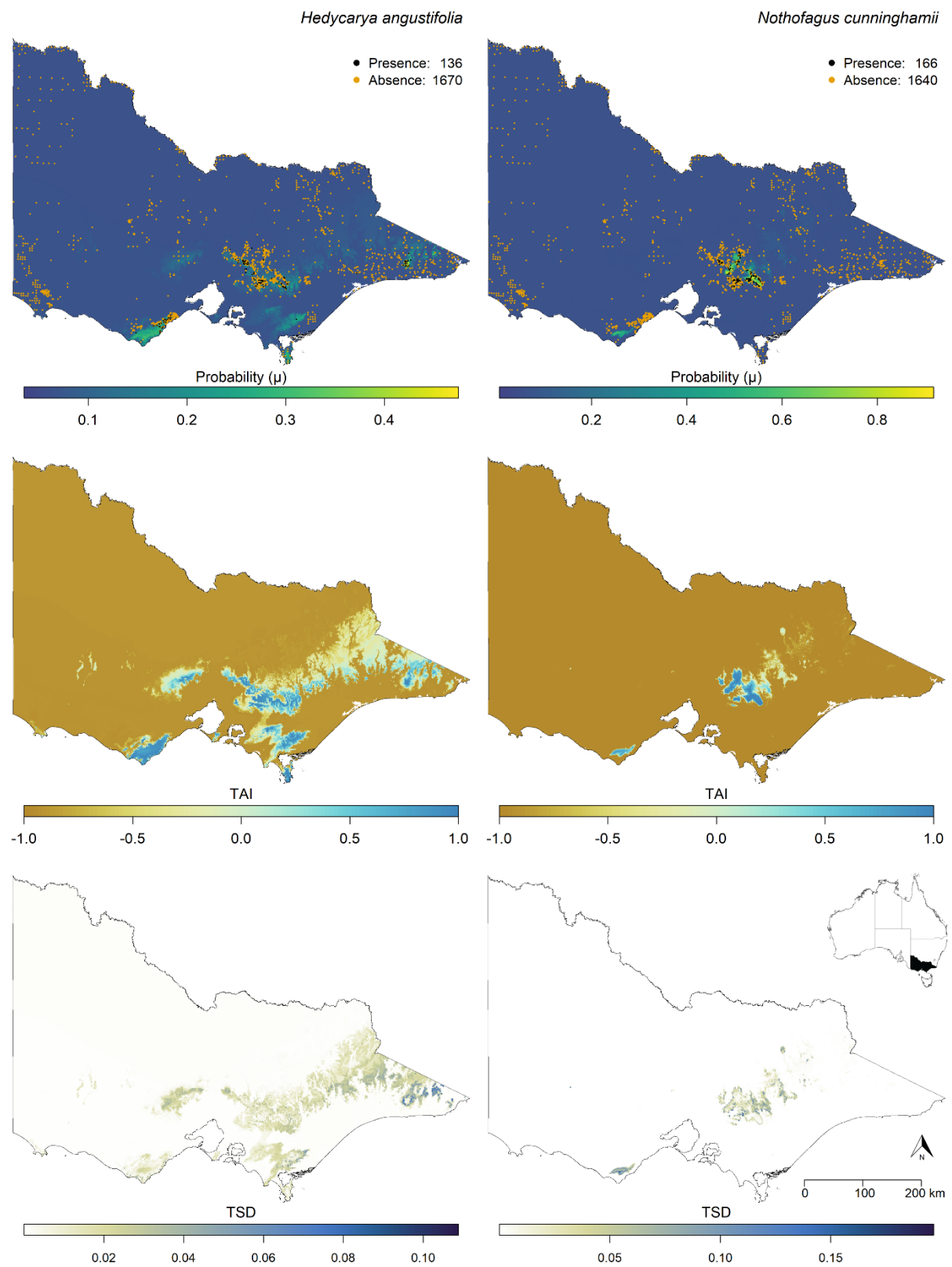


Figure 5.C.1: Continued.

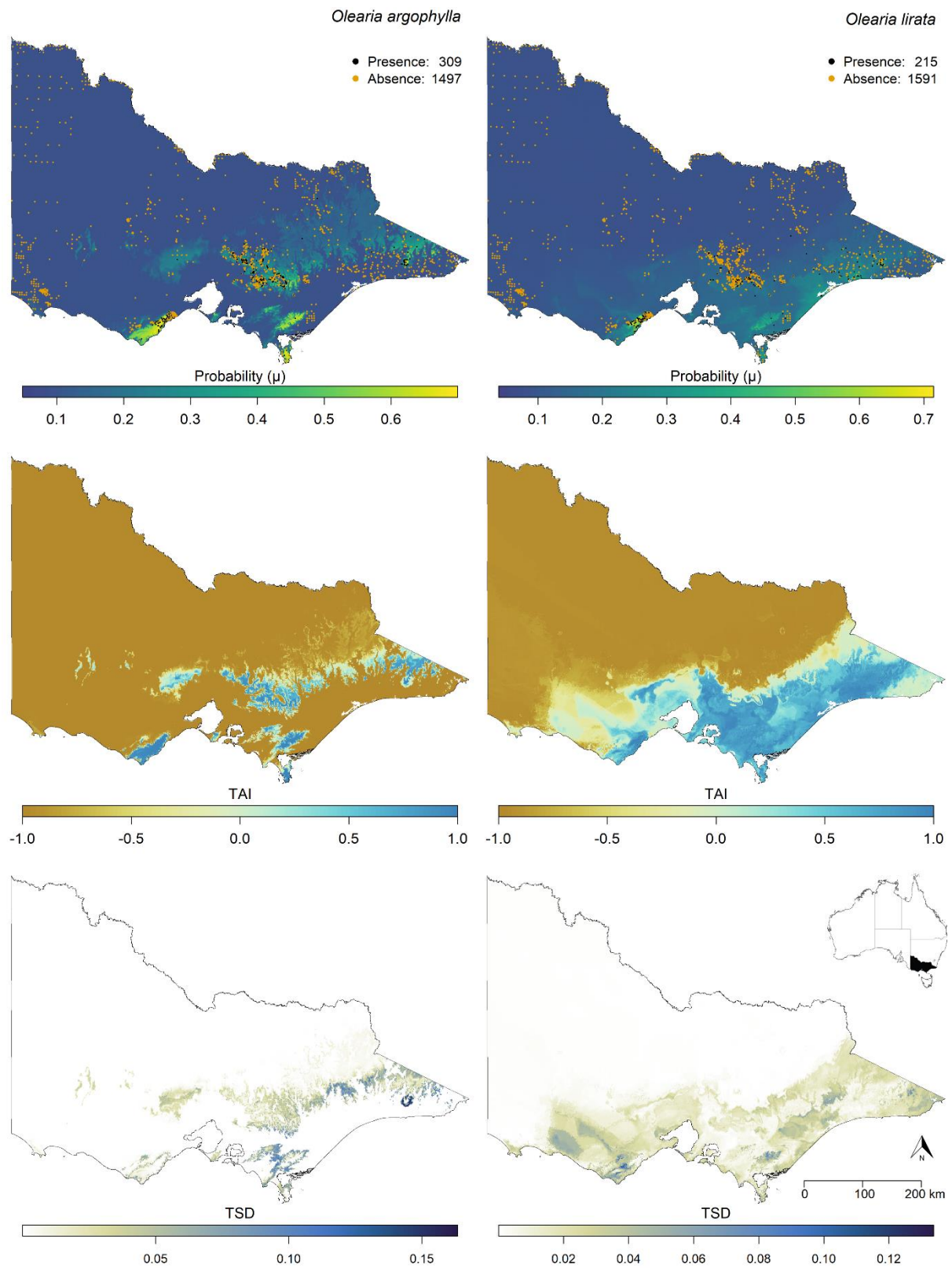


Figure 5.C.1: Continued.

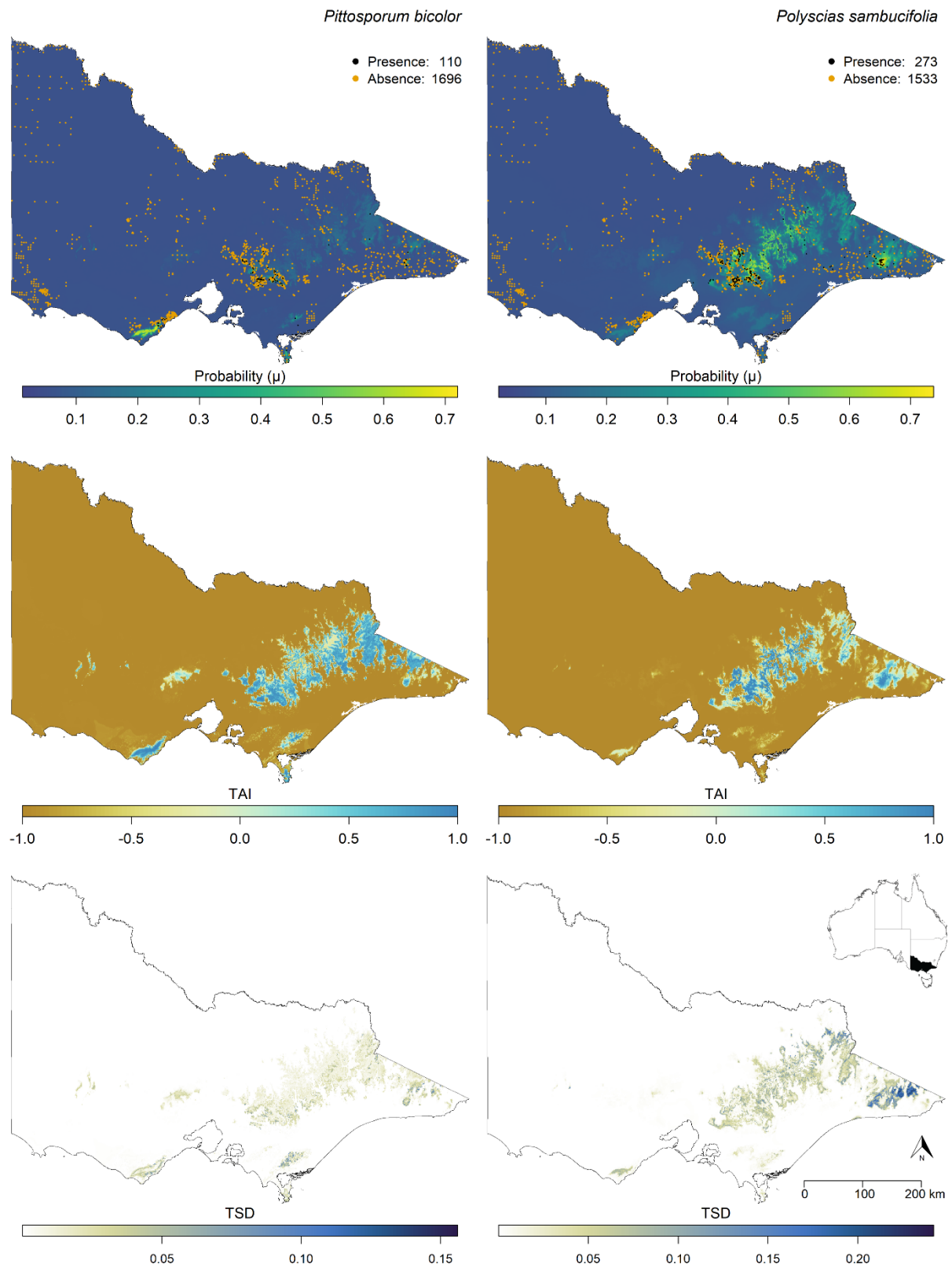


Figure 5.C.1: Continued.

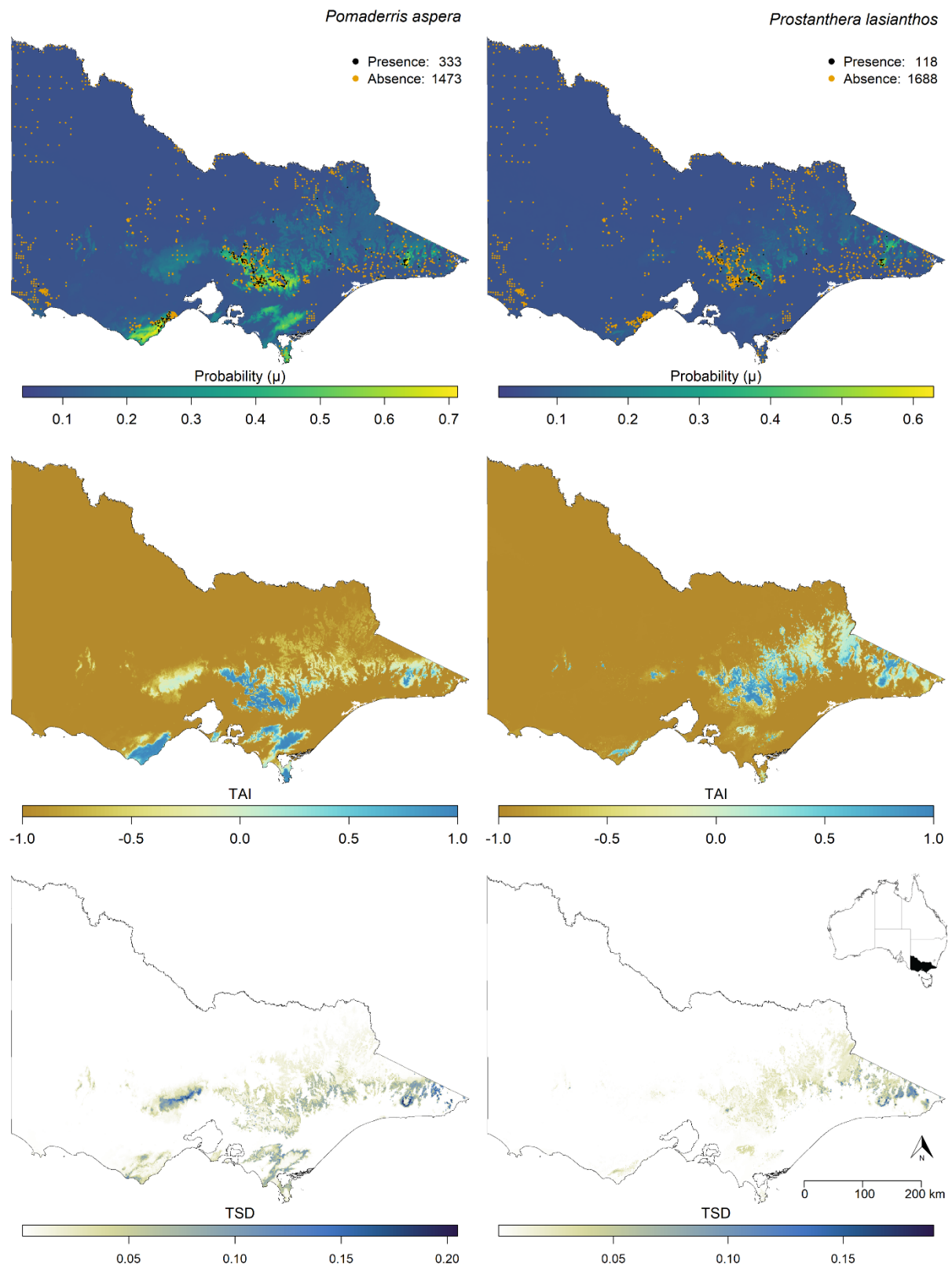


Figure 5.C.1: Continued.

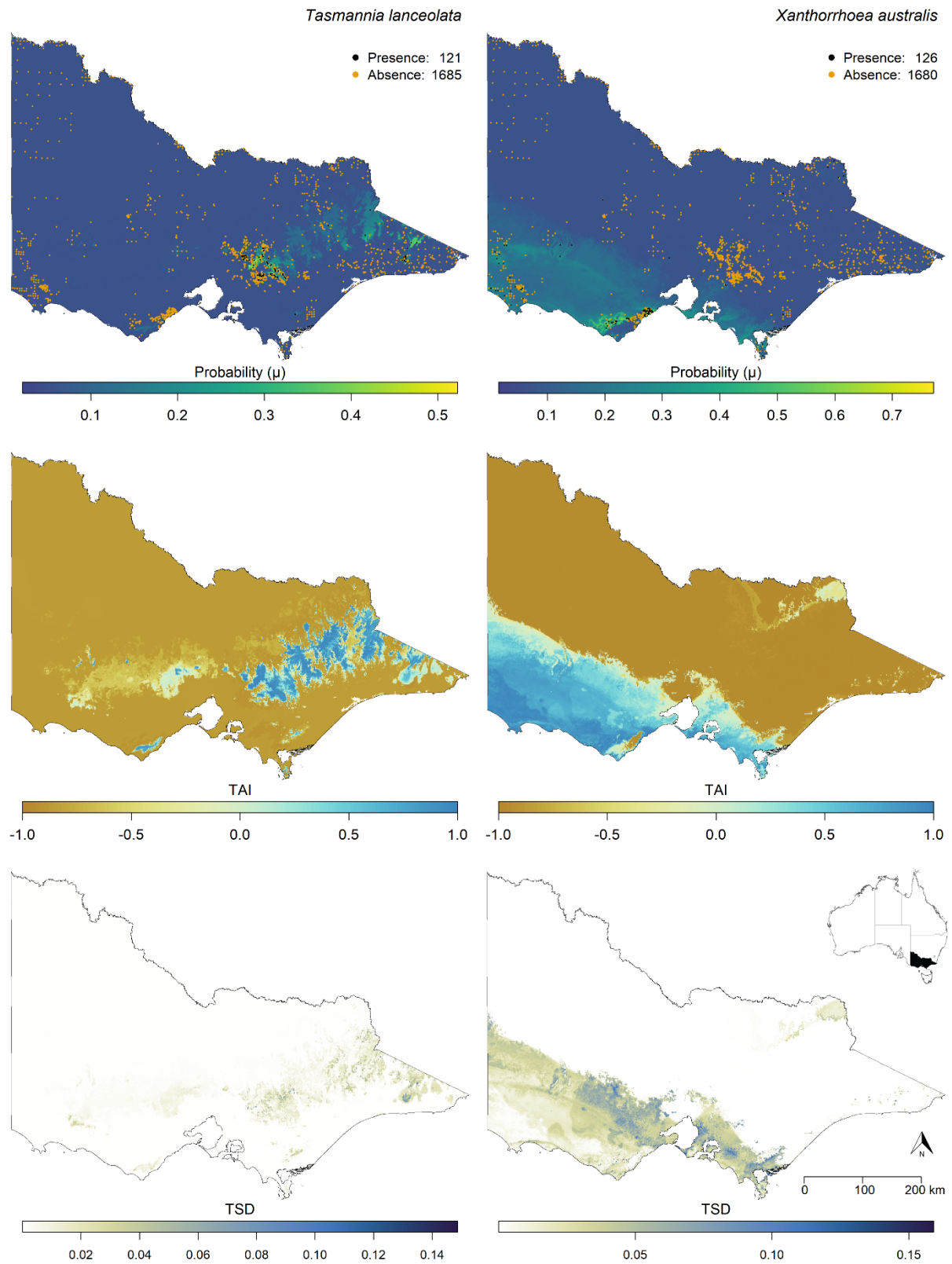


Figure 5.C.1: Continued.

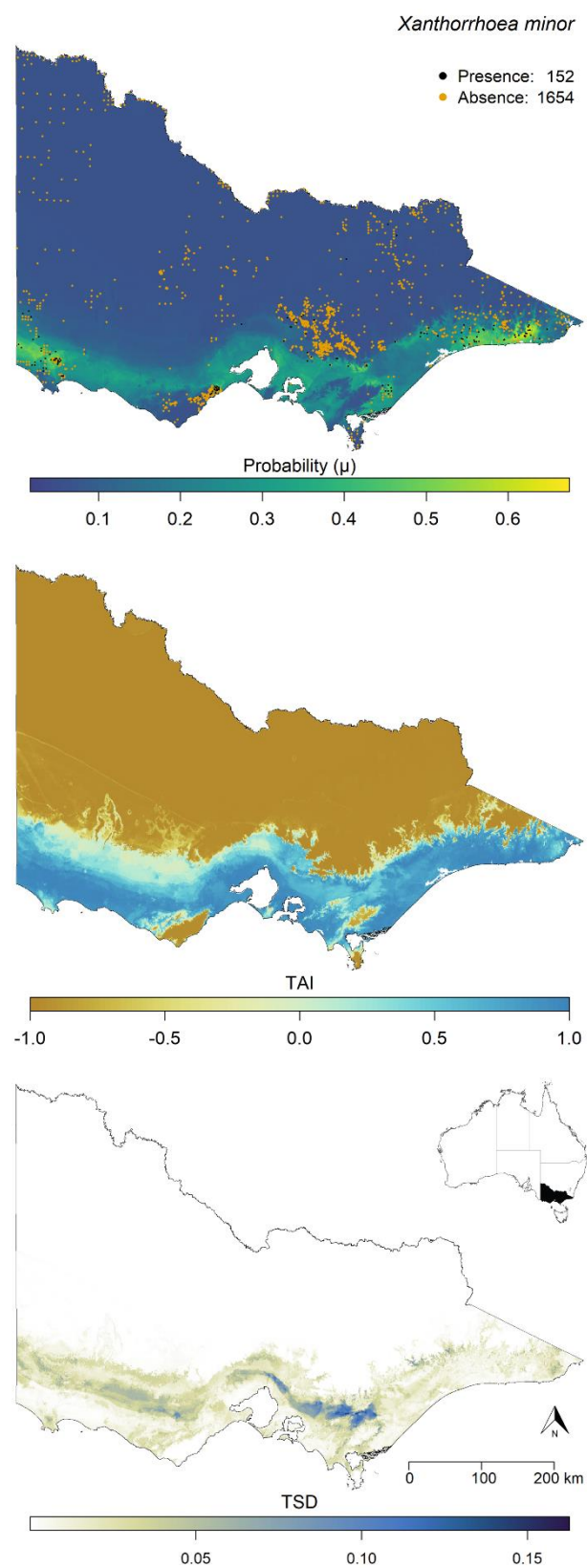


Figure 5.C.1: Continued.

6

CHAPTER SIX: CONCLUSIONS

The previous four chapters have described a series of methods for interpolating climate variables and evaluated how the spatial and temporal characteristics of these datasets can be used to improve the prediction of species distributions. This chapter begins with a summary of the findings from these analyses and addresses the aims and research questions which were set out in the introductory chapter. The implications and limitations of this research are subsequently discussed, followed by a series of recommendations for future studies.

6.1. SUMMARY OF FINDINGS

This research has identified, evaluated and applied several approaches for improving the performance of climate interpolations to generate datasets at ecologically relevant scales. A comparison of interpolation algorithms in southeast Australia (Stewart & Nitschke 2017/Chapter 2) corroborated the effectiveness of thin-plate splines for generating climate surfaces (Hutchinson & Gessler 1994). One of the great advantages of spline interpolation methods is that the smoothing parameter is estimated via generalised cross-validation, and therefore no a-priori estimation of the spatial covariance structure of the data is required. Partial spline models (which incorporate additional linear covariates) were evaluated in Victoria, southeast Australia and were subsequently assessed in the Royal Himalayan Kingdom of Bhutan to confirm their effectiveness in a novel environment with vastly different climatic conditions. Thermal remote sensing data and local topographic indices provided substantial improvements in minimum temperature interpolation performance across Victoria and were also highly effective when transferred to Bhutan. These improvements were consistent throughout the year in Victoria, but most effective during the winter months in Bhutan when inversions may more readily develop under clear, calm conditions with low relative humidity. Maximum temperature interpolations were also improved by thermal imagery across Victoria and Bhutan; however, the performance difference was generally more modest and most effective during the summer months. Thermal inversions contradict typical model assumptions regarding temperature lapse rates (i.e. temperature decreases with elevation) and are not

considered in most interpolation procedures. As these inversions typically develop in the early hours of the morning, night-time thermal imagery provides an excellent opportunity to represent these processes.

Each of the climate datasets generated demonstrated substantial differences from those which would otherwise have been available for Victoria or Bhutan. Alternate methods for interpolating minimum temperature (i.e. thermal remote sensing and topographic indices) allowed for a decoupling of the slope and valley atmospheres in the generated datasets and provided more realistic behaviours across regions of complex topography in both study regions. Temperature surfaces were therefore able to capture mesoscale inversion behaviour and the indirect effects of microclimate driven by land cover types at landscape scales. In Victoria, a comparison of regional interpolations with WorldClim (Hijmans et al. 2005) and AWAP (Jones et al. 2009) demonstrated considerable differences in temperature across regions of complex topography. Modelling maximum and minimum temperatures with different assumptions also had potentially large impacts on derived variables such as the diurnal temperature range. The extreme topographic variability of Bhutan resulted in large deviations from the WorldClim and CRU CL 2.0 (New et al. 2002) climatologies, with biases in mean annual temperature relative to local interpolations of over 2.5 °C and 10 °C, respectively. These differences were partially driven by the higher resolution digital elevation models (DEMs), temporal alignment of observations and the network of weather stations included (particularly in Bhutan, where global datasets do not use the local weather station network) in each of the regionally interpolated datasets. The regional analyses were therefore critical in demonstrating the effectiveness of alternate interpolation techniques, as the varying treatments could be controlled by using identical weather station observations and elevation data.

While improvements in temperature interpolation were the primary focus of this research, regional precipitation interpolations were also distinct from pre-existing climate datasets for both study regions. Precipitation surfaces in both Victoria and Bhutan were interpolated using a smoothed DEM to account for the lack of strong correlation with elevation at scales below 5 to 10 km (Hutchinson 1998, Sharples et al. 2005, Daly et al. 2007; Stewart et al. 2017/Chapter 3). This smoothing resulted in surfaces which lacked sharp gradients between neighbouring pixels and minimised over-fitting precipitation to elevation, which otherwise affects most Australian and global climate datasets. In Bhutan, the regional interpolations were able to capture the heavy precipitation that occurs in the southern foothills while predicting

semi-arid central valleys with wetter conditions at higher elevations. These effects are absent from the WorldClim and CRU CL 2.0 datasets which predict wet valleys and decreasing precipitation with elevation, leading to large biases of up to 3,000 mm in comparison to the regional data. These systematic biases demonstrate the magnitude of impact an insufficient observation density may have on interpolated climate surfaces.

The temporal characteristics of climate were quantified and evaluated for modelling plant species distributions using the datasets developed for Victoria at high spatial and temporal resolutions. Generalised Extreme Value (GEV) distributions (Fisher & Tippet 1928) were used to characterise the frequency and magnitude of extremes at multi-decadal timescales. GEV distributions are well suited to represent the rarest, most severe conditions, unlike typical extreme indices (e.g. counts of days beyond thresholds, percentiles, etc.) that represent moderate severity extremes with short return intervals (Wang et al. 2013). The expected return intervals of the hottest and driest summers, and coldest winters are best represented by considering the asymmetrical nature of extremes which can be achieved using the GEV distribution. Annual extremes and corresponding measures of interannual variability derived using alternate expected return intervals led to moderate but significant improvements in the statistical performance of distribution models in the assessment of 37 plant species. Both isotropic (i.e. the scale parameter, analogous to the standard deviation) and asymmetric (i.e. the distance between a typical annual extreme and one of an increased magnitude with lower frequency) measures of extreme variability improved model performance with a random cross-validation. This result was consistent with earlier findings by Zimmerman (et al. 2009); however, only asymmetric variability retained a significant improvement in model performance when extrapolating to new space via spatially blocked cross-validation. Interannual variability metrics commonly influenced the outer limits of predicted species distributions. The statistically optimal distribution for each species was identified by iterating through varying expected extreme return intervals which acted to shift the leading and trailing edge of predictions.

The importance of selecting a suitable climate dataset for correlative species distribution models (SDMs) was evaluated using data from three alternate interpolation techniques in Victoria (Stewart & Nitschke 2017/Chapter 2; Chapter 4), in addition to two versions of the WorldClim dataset (Hijmans et al. 2005; Fick & Hijmans 2017). Spatial covariates for each of the Victorian datasets were represented as either monthly mean

climatologies or derived from extreme value statistics using time-series temperature and precipitation data. Each of the 37 plant species modelled previously using GEV distributions were used to assess these alternate climate predictors. The regional Victorian datasets provided significantly improved model performance relative to the original WorldClim dataset and trended towards better performance relative to WorldClim v2. Performance among the regional Victorian datasets was very similar and no statistically significant trends were detected, despite the improvements in interpolation performance for minimum and maximum temperature surfaces. Most models were dominated by responses to the moisture index which was calculated as a function of mean temperature and precipitation, and therefore may have diluted the impact of the improved temperature interpolations.

Multi-model ensembles using alternate climate datasets provided large improvements in the predictive performance of plant SDMs. Ensembles outperformed individual models in 89% of all cases and provided the highest predictive performance for 16 of 37 plant species assessed. These results indicate that multi-model ensembles which utilise alternate climate datasets provide a pragmatic way to improve the predictive performance of SDMs. The Threshold Agreement Index (TAI) and Threshold-scaled Standard Deviation (TSD) were developed to support the interpretation of ensemble predictions by summarising the behaviour of contributing models. These supporting variables describe the level of agreement among competing models and identify regions which are associated with the highest amount of uncertainty or would have been most at risk of an erroneous prediction had only one climate dataset been selected.

6.2. IMPLICATIONS AND LIMITATIONS

This research has demonstrated a reproducible methodology for generating climate variables at ecologically relevant spatial and temporal scales using regional weather station networks. Many parts of the world have long term weather observations that can be used to reproduce these techniques. While this is a time-consuming process, local interpolations allow for more focus to be placed on carefully pre-processing the input data and producing a high-quality product suitable for the required application. The datasets generated for both Victoria and Bhutan showed clear advantages over alternative gridded data sources as a function of spatial resolution, observational data and interpolation techniques. While statistical

downscaling methods (e.g. Karger et al. 2017) may provide a means of addressing disparities in spatial resolution, the full range of improvements demonstrated as part of this research would be difficult to achieve without calibrating interpolations directly using station records and supporting secondary surfaces (e.g. thermal remote sensing data, topographic indices of relative elevation). Climate datasets can vary considerably given the number of decisions that must be made as part of the modelling process. The strengths, weaknesses and biases in datasets arising from these decisions may become compounded when modifying pre-existing gridded products.

The divergent behaviour of maximum and minimum temperature interpolations will have an impact on the accuracy of bioclimatic indices and derived meteorological variables. Diurnal temperature ranges in Victoria demonstrated the considerable biases which could arise between datasets when accounting for temperature inversions and the indirect effects of microclimate driven by land cover. As temperature is a key input to many ecologically important variables such as potential evapotranspiration, vapour pressure deficit and bioclimatic indices, these biases may have large subsequent impacts on how climate and meteorological variables are characterised. These impacts will most likely be greatest across topographically complex terrain, particularly in places such as Bhutan where there were spatially autocorrelated biases of up to 5°C across competing regional interpolations of minimum temperature.

Several issues suggest that the topographic index, as implemented in Chapters 2 and 3, may be limited in characterising temperature inversions at broad landscape scales despite the improvement in statistical performance that was achieved. The optimal focal range used for calibrating the index in Bhutan (8.8 km) was over five times greater than in Victoria (1.25 km). Furthermore, there was also a divergence in the optimal focal range for the topographic index in Bhutan as spatial scale increased. This suggests that there are potentially issues with the parameterisation of this variable and the calibration of the linear sub-models that form part of the interpolation. Differences in the optimal focal range may in part be driven by the influence of secondary factors such as the relative scale of topographic features (elevations of up to 2 km and 7.5 km in Victoria and Bhutan, respectively) and associated elevation gradients, and differences in wind, humidity and cloud cover regimes. Divergence in the optimal focal range in Bhutan, when assessed in conjunction with MODIS LST, is perhaps not surprising though given that these variables appear to characterise the same physical processes. The optimal focal

range would be strongly influenced by the component of variability that is not explained by the remote sensing data because of this interaction. The use of MODIS LST dampened the influence of the topographic index in both study regions though, and therefore would have constrained these limitations to some degree. Nevertheless, these findings suggest that further work is required to ensure that local topographic indices adequately represent cold air drainage, pooling, and thermal inversion processes at landscape scales and in differing climatic regimes. Multi-scale techniques that allow for spatially varying dependence may be critical in developing a more generalisable approach.

Another limitation of the methods developed as part of this study is that the time-series temperature products are derived using an interpolation of anomalies relative to a 30-year climatology. This approach was taken to provide more stable predictions and to minimise bias arising from temporal misalignments in weather station observations; however, it is not likely that remote sensing imagery and cold air pooling regimes will remain stable over time. For example, the MODIS imagery and Land Surface Temperature (LST) algorithm (Wan et al. 2015) is sensitive to land cover dynamics which cannot be characterised using a long-term mean. Similarly, cold air drainage and pooling is an ephemeral process (Daly et al. 2009) which is dependent upon factors such as humidity, cloud cover and wind that affect the surface energy balance (Stewart et al. 2017/Chapter 3). The anomaly approach cannot represent variability in these factors, and therefore it likely that minimum temperature will be underestimated on inversion nights and overestimated on non-inversion nights where these processes are only represented by a climatology. While MODIS LST 8-day composite imagery is available, the scenes frequently include missing pixels due to cloud cover and quality control processes. Furthermore, there can be spatial artefacts which arise from the compositing procedure, for example, when multiple days of different weather conditions within the 8-day window are aggregated together. These limitations required a monthly mean aggregation of imagery to produce stable interpolated surfaces. Similar issues were noted by Fick & Hijmans (2017) in the development of the monthly mean WorldClim 2 surfaces, which were addressed using a gap-filled 5 km MODIS LST product in their interpolations.

Interannual variability of ecologically important meteorological variables is likely to be an important component of the niche (Suggit et al. 2017); however, it is rarely considered in correlative SDM studies. The GEV distribution provides a statistically robust mechanism for characterising the distribution of extremes (Coles 2001) and can quantify conditions which

are likely to have some of the greatest ecological impacts (e.g. hottest, coldest or driest periods). Some studies have promoted the use of extreme value theory in ecology (Gaines & Denny 1993; Katz et al. 2005) but applications in the SDM literature remain rare. While the improvement in statistical performance provided by interannual variability of extremes was not always large, it was significant, and the spatial configuration of predicted distributions was often changed considerably. Varying the expected return intervals of hot, dry, and cold extremes commonly resulted in varying predictions around the leading and trailing edge of plant species distributions, indicating that the fitted distribution of extremes can be utilised to improve model calibration. Climate scientists expect that the distribution of extreme weather will change over the coming decades (Katz & Brown 1992; Orlowsky & Senviratne 2012), and therefore SDMs will not be able to fully capture these trends by only accounting for shifts in mean conditions. The methods developed as part of Chapter 4 provide statistically robust techniques for characterising climate extremes that can potentially improve the link between contemporary datasets and climate change projections.

Despite the apparent benefits of using the GEV distribution to characterise extreme events there are several barriers and limitations that may limit its application. Fitting the GEV distribution first requires long term time series climate data. While this is in of itself not a large limitation, the space-time resolution trade-off common to most datasets means that the data will often be limited in at least one dimension. The datasets that were developed as part of this study were therefore critical in developing high resolution GEV-derived extreme variables. One of the drawbacks of these datasets for characterising extremes is that they are developed using interpolated anomalies relative to a reference climatology (discussed above, and especially relevant for temperature inversions). This limits the ability of time-series variability to be characterised at fine scales; however, it is a typical limitation of climate datasets. Generating GEV-derived variables can also be very computationally expensive, especially with large datasets; however, the *extRemes* package for R (Gilleland & Katz 2016) provides a valuable set of tools to facilitate the process. The analyses presented in Chapter 4 used the block maxima technique for fitting monthly extremes; however, there are alternate options for generating extreme value distributions such as the peaks over threshold (POT) method that fits the distribution of extremes beyond a threshold value using the Generalised Pareto Distribution. While the POT method is likely to make effective use of high frequency data (e.g. daily), selecting appropriate thresholds in SDM applications is likely to be difficult without species-specific knowledge.

Climate dataset selection has a large impact on spatial predictions and the statistical performance of SDMs. Alternate climate datasets are each associated with their own strengths, weaknesses and biases that arise as part of the modelling procedure. Many decisions must be made when generating new datasets that affect the quality of the resulting surfaces. Despite these differences, the analyses in Chapter 5 demonstrate how the predictive performance of SDMs may not always be directly attributable to the (perceived or otherwise) quality of climate data used for modelling. There was a general lack of consistency in which dataset performed best across species; however, multi-model ensembles performed better than 89% of individual models and had the best statistical performance for close to half of the species evaluated. Multi-model ensembles allow for the strengths and weaknesses of models calibrated with alternate climate datasets to be traded-off against one another. These results strongly suggest that comparative studies of climate predictors for SDMs should focus not only on which dataset may perform better than another, but also on how they may complement one another. Multi-model ensembles which utilise the expanding number of available climate datasets will allow for a pragmatic approach to dataset selection while building robust predictions of species distributions.

This research specifically targeted a subset of the available climate datasets for fitting SDMs across southeast Australia. These included alternate regional interpolations for Victoria and both WorldClim datasets, each of which were interpolated using thin plate spline methods. The Victorian datasets were specifically developed to provide a contrast between common interpolation methods (full spline dependence on latitude, longitude and elevation) and those which use secondary topographic information or remote sensing data. The only analogue to this comparison was the global WorldClim datasets, which use varying combinations of latitude, longitude, elevation, coastal proximity and remote sensing data for calibration (Chapter 5). Another important reason for selecting the WorldClim datasets was that they are by far the most widely used datasets in the SDM literature. This research may have benefitted from the use of some additional datasets; however, the results may have become confounded due to large disparities in spatial resolutions (Jeffrey et al. 2001; Jones et al. 2009; Harris et al. 2014), interpolation methods and dataset independence (e.g. Kriticos et al. 2012; Karger et al. 2017;) and likely deficiencies in the study area (e.g. Funk et al. 2015).

6.3. RECOMMENDATIONS FOR FUTURE RESEARCH

Several potential avenues for future research have arisen as part of this work. Building improved climate surfaces at fine scales is likely to remain an active area of research given the importance of such datasets for ecological studies. The predictive performance of climate interpolations is likely to benefit from more focus on the temporal components of variability. For example, minimum temperature interpolations may be improved using higher frequency satellite observations with the use of spatio-temporal gap filling techniques (e.g. Van Neil et al. 2017) or by using empirical equations to post-process the data (e.g. Karger et al. 2017). It is unclear at this stage, however, if the spatial and temporal coherence of the MODIS LST imagery would allow for interpolations of comparable quality with the anomaly plus climatology method used in this research. Developing robust methods that can characterise the ephemeral nature of temperature inversions at landscape scales will likely be particularly useful, especially if this can be achieved in the absence of remote sensing data that would otherwise limit the temporal extent over which interpolations could be applied. If successful, such methods may open opportunities to extract more detail from extreme surfaces derived from the GEV distribution, with potentially important implications for SDM applications.

The impact of temporal variability on the predictive performance of SDMs has rarely been evaluated in the literature. Climate change projections indicate shifts in both the mean and the distribution of meteorological variables, and therefore extreme value theory may be critical for the development of robust new methods for linking ecological models to climate data. Further investigation of different taxa in more diverse regions of the world would strengthen the findings presented by Zimmerman (et al. 2009) and in Chapter 4, providing additional support for considering temporal variability in correlative SDM applications. Extreme value theory could also be utilised in alternate ways to develop new variables or more specifically target species-specific tolerances.

When comparing the predictive performance of SDMs calibrated using alternate climate datasets, most studies have focused on identifying the best set of inputs. The results of Chapter 5 demonstrate that considerable opportunities to improve SDMs may be achieved simply by building ensembles of available datasets. Future studies would benefit by evaluating the predictive performance of SDM ensembles using other climate datasets not evaluated as

part of this research. Furthermore, the TAI and TSD metrics which were developed would benefit from further testing in alternate scenarios to validate their effectiveness in characterising ensemble behaviour.

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7

APPENDIX A: ACCEPTED PUBLICATIONS FROM THESIS

APPENDIX A.1: STEWART SB, NITSCHKE CR. 2017. IMPROVING TEMPERATURE INTERPOLATION USING MODIS LST AND LOCAL TOPOGRAPHY: A COMPARISON OF METHODS IN SOUTH EAST AUSTRALIA. INTERNATIONAL JOURNAL OF CLIMATOLOGY 37(7): 3098–3110. DOI: 10.1002/JOC.4902.

Improving temperature interpolation using MODIS LST and local topography: a comparison of methods in south east Australia

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ABSTRACT: Available climate data for south east Australia is reliant upon elevational lapse rates, which do not account for mesoscale processes that can affect temperatures, such as cold air drainage. Additional predictor variables are available for generating new climate datasets such as topographic indices and Moderate Resolution Imaging Spectroradiometer land surface temperature (MODIS LST); however, these have not been thoroughly tested to date. In this study, the relative benefits of including a localized topographic index and standardized MODIS LST values for temperature interpolation were assessed using partial bivariate splines, full and partial trivariate splines, and regression kriging. Trivariate splines provided the best interpolation performance in most cases; however, the partial bivariate spline with a fixed dependence upon elevation performed marginally better than the full trivariate spline for minimum temperature. The local topographic index improved the RMSE of minimum temperature climate normals by 17% in comparison to the best performing elevation only model. A further improvement for minimum temperature performance was achieved by including standardized night time MODIS LST values as covariates (34–39% reduction in RMSE). Standardized day time MODIS LST values improved maximum temperature interpolation performance; however, the improvement was only marginal in comparison to the full trivariate spline (6% reduction in RMSE). Cross validation of daily maximum and minimum temperature anomalies reflected performance trends shown in the climate normal analysis. Results suggest that the use of alternative approaches to interpolating temperature data may have significant implications for the calculation of bioclimatic variables and provide new opportunities to study extremes at high spatial and temporal resolutions using existing weather station networks. Furthermore, improving minimum temperature surfaces by accounting for temperature inversions driven by cold air drainage regimes may improve our ability to incorporate mesoscale temperature variability into a variety of applications, such as deriving temperature dependent climatic variables, species distribution modelling and assessments of fire risk.

KEY WORDS climate; temperature; interpolation; kriging; splines; MODIS; topography; cold air drainage

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1. Introduction

Interpolated climate datasets are a core component in a broad range of applications, from fire modelling and calculation of drought indices, to ecological assessments, species distribution modelling and agricultural assessments. Gridded climate datasets utilizing macroscale elevational gradients are readily available at global and continental scales (Jeffrey *et al.*, 2001; Hijmans *et al.*, 2005; Haylock *et al.*, 2008; Hutchinson *et al.*, 2009; Jones *et al.*, 2009). Bioclimatic variables such as mean annual temperature and precipitation, annual diurnal range and maximum temperature of the driest quarter have been heavily utilized in species distribution modelling and ecological assessments since the 1980s (Booth, 1985; Nix and Busby, 1986; Elith and Franklin, 2013). Over 20% of Eucalypt species persist in regions that vary by less than

1 °C in mean annual temperature (Hughes *et al.*, 1996), which highlights the importance of using high quality climate data for ecological studies. The calibration and spatial resolution of prediction surfaces, however, may mask the effect of topographic complexity on climate and lead to the homogenisation of spatial variability across landscapes. This homogenisation may have implications for species distribution modelling, which can require fine scale characterisation of climatic variables to reliably represent the fundamental or realized niche of a species (Kearney *et al.*, 2010). Spatial homogenisation may also restrict the predictability of climatic refugia that can allow organisms to persist in regions that would otherwise be unexpected (Ashcroft *et al.*, 2012). Climatic refugia tend to exist within heterogeneous landscapes with diverse topographic and edaphic conditions (Kirkpatrick and Fowler, 1998; Burke, 2002). Riparian corridors, e.g. have acted as refugia for mesic species during droughts and fires associated with past climatic events (Aide and Rivera, 1998; Rouget *et al.*, 2003).

Gridded climate data are commonly interpolated using point locations (Hutchinson, 1995; Jeffrey *et al.*, 2001;

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Hijmans *et al.*, 2005; Hutchinson *et al.*, 2009; Jones *et al.*, 2009) or generated by downscaling coarse data using methods such as those described by Wang *et al.* (2012, 2016) that apply elevational lapse rates against a high resolution digital elevation model (DEM). Many alternate methods exist for interpolating climate data, including kriging, thin plate splines, regional regressions and process based microclimate models.

The kriging system of linear equations for geostatistical interpolation is covered in detail by Cressie (1993), Hengl (2009) and Bivand *et al.* (2013). The value at an unknown location is calculated by the weighted sum of the surrounding observations. These weights are determined by solving the kriging system, which requires the covariance structure of the observations to be modelled prior to interpolation. The covariance function is represented through the variogram; a valid positive-definite model (i.e. linear, spherical, exponential, etc.) fit through semivariance values calculated for binned observations at increasing lag distances. The choice of variogram model is a non-trivial process that requires consideration beyond minimizing the sum of squares (Cressie, 1989; Cressie and Zimmerman, 1992). For example, a Gaussian variogram model exhibits parabolic behaviour near the origin and can lead to instability in the kriging system where there are large differences that occur between values at short ranges. Furthermore, a poorly defined autocorrelation structure may result in a variogram with insufficient range, leading to spatial artefacts (i.e. 'bullseye' patterns) and defaulting to the mean in regions where observations are too distant from the prediction location. Kriging has been directly compared against spline interpolation in several studies (Hutchinson and Gessler, 1994; Laslett, 1994; Boer *et al.*, 2001; Hofstra *et al.*, 2008); however, the performance of any given interpolation method is heavily dependent upon the availability of suitable and representative sample data (Isaaks and Srivastava, 1989; Li and Heap, 2014).

Thin plate splines (Wahba, 1990; Hutchinson, 1995) are commonly used for geospatial interpolation of climate. The thin plate spline model consists of two main components; an affine component which fits the global trend as a function of spline variables (latitude and longitude for bivariate splines; latitude, longitude and elevation for trivariate splines), and a local non-affine component that adjusts the local non-linear surface. These components are fit to minimize the total amount of bending energy that is required to fit the spline surface. The regularization parameter allows for inexact interpolation by dictating the degree of smoothness in the spline surface and is commonly estimated using generalized cross validation (GCV; Craven and Wahba, 1979; Hutchinson and Xu, 2013). Partial thin plate splines also include a parametric regression component (Bates *et al.*, 1987) to incorporate additional independent covariates. Splines are commonly used for generating climate data as they are smooth interpolators (Hutchinson and Gessler, 1994), can be readily automated as no initial analysis of spatial dependence is required, and are easily implemented given the availability of robust, purpose built software such as ANUSPLIN (Hutchinson and Xu,

2013) and ANUCLIM (Xu and Hutchinson, 2011). Trivariate splines are often preferred for climatological analyses as they allow for a spatially varying dependence upon elevation (Hutchinson, 1995; Hutchinson *et al.*, 2009). Spline based interpolation methods have been used to generate global and continental scale climate datasets; however, these datasets often involve a trade-off between spatial and temporal resolution.

The SILO (Jeffrey *et al.*, 2001) and Australian Water Availability Project (AWAP; Jones *et al.*, 2009) datasets use spline-based methods for interpolating climate variables (with the exception of SILO precipitation which uses ordinary kriging for precipitation) across Australia at daily, monthly and further aggregated temporal resolutions. Both provide daily data at a spatial resolution of approximately 5 km across Australia, with long term provisional climate normals (monthly aggregated observations having sufficient number of observations to represent the 30 year normal period) available at a slightly higher resolution of approximately 2.5 km in the AWAP dataset. Climate observations are interpolated directly based on the target temporal resolution in the SILO dataset. The AWAP dataset utilizes the anomaly approach, whereby provisional climate normals (hereafter referred to as climate normals) and climate anomalies (deviation from mean conditions) are interpolated separately and combined to form the final prediction surfaces. The anomaly approach employed by the AWAP method was reported to improve cross validation error statistics by approximately 40% in comparison to the direct approach (Jones *et al.*, 2009), which supports earlier recommendations to interpolate anomalies rather than raw observation data (Jones and Hulme, 1996).

WorldClim surfaces were developed using trivariate splines to provide a high spatial resolution (approximately 860 m) and globally consistent database of mean monthly temperature and precipitation values for 1950–2000 (Hijmans *et al.*, 2005). Globally representative climate datasets prior to this study were relatively coarse in spatial resolution, ranging from 18.5 (New *et al.*, 2002) to 55.6 km (Leemans and Cramer, 1991; Mitchell and Jones, 2005) at the equator. The CliMond database (Kriticos *et al.*, 2012) combines WorldClim and CRU data (New *et al.*, 1999, 2002). The WorldClim dataset and derived bioclimatic variables have been heavily used in correlative species distribution models (Leathwick and Austin, 2001; Elith and Franklin, 2013; Kuttywayo *et al.*, 2013; Guo *et al.*, 2015; Gelviz-Gelvez *et al.*, 2015) due to their relatively high resolution and global consistency.

Kriging based climate analyses have been investigated more commonly in Europe (Dobesch *et al.*, 2007; Ly *et al.*, 2011). Hofstra *et al.* (2008) demonstrated that kriging with a global variogram fit and an external drift component performed better on average than five alternative methods (including spline based methods) when interpolating climate variables across the United Kingdom. The E-OBS dataset (Haylock *et al.*, 2008), however, is calibrated based on European climate normals interpolated using trivariate splines. Hengl *et al.* (2012) investigated the potential

for spatiotemporal regression kriging (RK) of daily temperature in Croatia using a time series of Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) mosaics. While limited somewhat by the 8-day temporal resolution of the composite MOD11A2 product (in order to minimize the effect of missing data), the final surfaces generated incorporate microclimatic factors driven by land use, such as the urban heat island effect and forest cover, which cannot be detected using topographical data alone.

In North America, the PRISM model (Daly *et al.*, 2002) provides a statistical framework for incorporating expert knowledge into climate mapping. The effect of orography on precipitation, elevation gradients, atmospheric interactions and coastal distance are all modelled within the PRISM framework. The ClimateWNA and ClimateAP models (Wang *et al.*, 2012, 2016) are used to downscale pre-existing climate datasets (such as those generated by PRISM and WorldClim) using a combination of bilinear interpolation and elevational lapse rates. This downscaling allows for the generation of climate data at spatial resolutions limited only by the fidelity of the input DEM. This approach is limited given that macroscale elevational gradients used to generate coarse resolution climate data cannot effectively account for mesoscale processes such as cold air drainage due to the scale of the initial interpolated surface. Alternatively, software packages such as ANUSPLIN (Hutchinson and Xu, 2013) and ANUCLIM (Xu and Hutchinson, 2011) can be used to generate climate data at spatial grain only limited by the resolution of the input DEM.

Regional regression and processed based modelling techniques can also be used to generate very high fidelity climate datasets of varying spatial and temporal resolution. Regional regression models that incorporate the additional drivers of climate such as slope, aspect and vegetation cover, however, require extensive field based campaigns to capture highly variable *in-situ* conditions (e.g. across multiple forest types, shade classes, slopes, aspects) that would not otherwise be possible using the historical network of standardized weather stations (Ashcroft and Gollan, 2012; Hardwick *et al.*, 2015). Process based equations such as those implemented by MT-CLIM can be used to downscale coarse resolution climate data or interpolate point observations by applying elevational lapse rates, correcting for the ratio of solar radiation on a sloped surface to that of a flat surface and adjusting for the effects of vegetation cover (Running *et al.*, 1987; Moore *et al.*, 1993; Nyman *et al.*, 2014). Process based models, such as Niche Mapper, are also able to disaggregate daily data into hourly predictions using a broad range of climatic drivers as input variables; however, these models do not correct for mesoscale processes such as cold air drainage (Kearney *et al.*, 2014).

Opportunities exist to improve temperature interpolation by incorporating local topography and remotely sensed LST data into prediction surfaces. The MODIS LST algorithm and workflow for the 8-day composite product (MOD11A2) includes atmospheric correction, cloud masking, quality control and correction factors for

quarterly land use (MOD12Q1) and daily snow cover (MOD10_L2; Snyder *et al.*, 1998; Wan, 2006), which facilitates use in such studies. A significant advantage of this remote sensing data is the ability to quantify the thermal properties of heterogeneous landscapes at broad spatial scales. Topographic indices have also proven effective in improving minimum temperature interpolation performance using historical weather station networks (Daly *et al.*, 2007, 2009) and field based temperature loggers (Ashcroft and Gollan, 2012). The use of localized topography based metrics allows for local cold air drainage regimes, where cool dense air from higher elevation flows downslope and pools in topographic depressions overnight, to be quantified. Studies using topographic metrics for interpolation have focused on relatively coarse (4 km) or very fine (25 m) resolution topography. Additional testing at fine to intermediate scales using historical weather station networks is required to further explore the utility of these metrics.

This research assesses multiple interpolation methods using predictor variables that are compatible with the existing historical weather station network to provide novel temperature datasets for Victoria, south east Australia. Interpolating temperature surfaces at high resolution provides opportunities to capture the effects of mesoscale processes that may not otherwise be possible at coarser resolutions or via downscaling approaches. The use of the existing long term climate observation record and anomaly interpolation also allows for the generation of daily surfaces at broad temporal scales. The objective of this research is to assess the relative improvement in temperature surfaces that can be achieved by incorporating thermal remote sensing data and localized topography as independent covariates, and to identify the optimal interpolation algorithm for including these predictors. Daily climate data is required for many applications, and accounting for mesoscale processes will assist in bridging the gap between statistical interpolation routines and process-based models without the need for additional post-processing.

2. Method

2.1. Study extent

The state of Victoria is located in south east Australia (141°–150°E, 34°–39°S) with a total land surface area of 227 416 km² that ranges between 0 m and 1980 m in elevation above sea level. Topography becomes increasingly variable in the north eastern region of the state due to the location of the Australian Alps (Figure 1). Throughout the study period (January 1981 to August 2014) there were 140 weather stations recording temperature across Victoria, with a mean minimum separation distance of 18.7 km.

2.2. Datasets

Daily temperature records between January 1981 and August 2014, obtained from the SILO Patched Point Dataset (Jeffrey *et al.*, 2001), were used in the study. All

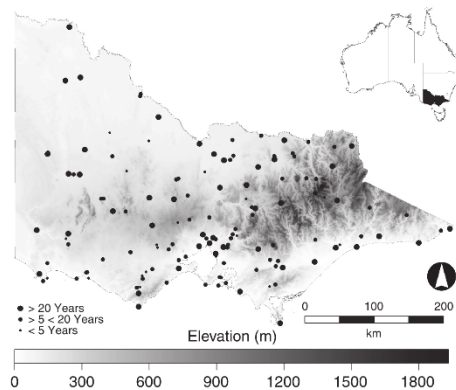


Figure 1. Digital elevation model of Victoria, Australia (Fenner School of Environment and Society and Geoscience Australia, 2008) and the network of temperature observations recorded between January 1981 and August 2014.

interpolated observations were removed prior to analysis. Latitude, longitude and elevation were acquired directly from weather station metadata provided with the SILO Patched Point Dataset for maximum and minimum temperature. Temperature prediction surfaces were calculated using the GEODATA 9 Second (approximately 250 m cell resolution) DEM Version 3 (Fenner School of Environment and Society and Geoscience Australia, 2008).

A localized topographic index was used to test for the effects of fine scale topographic complexity that drive temperature inversions due to cold air drainage regimes. The topographic index was used for modelling minimum temperatures but not for maximum temperatures due to coefficient instability between months and the limited effects of cold air drainage on summer maximum temperatures (Daly, 2006). This index was calculated as the difference between elevation at each DEM cell and the focal minimum (Daly *et al.*, 2007, 2009; Ashcroft and Gollan, 2012). To determine the optimal focal range, a series of search diameters between 750 m and 4.25 km were assessed using regression analysis. A search diameter of 1.25 km was selected to maximize the amount of variance explained while ensuring a sufficient number of cells were used in the analysis. A square root transform was applied to the topographic index to improve normality of model residuals and to limit the number of extremes in prediction surfaces caused by large but infrequent elevational gradients present across the landscape.

Remotely sensed MODIS LST data acquired between March 2000 and December 2010 were used to construct standardized monthly surfaces for day time and night time LST. Australia-wide composite mosaics of the MOD11A2 8-day LST collection five product (approximately 1 km cell resolution; Land Processes Distributed Active Archive Center (LP DAAC), 2014; Paget and King, 2008) were obtained from the AusCover Remote Sensing Data Facility

(www.auscover.org.au) and subset to the extent of Victoria. Daily MODIS LST images were frequently missing large amounts of data due to cloud cover, atmospheric conditions and quality control processes, therefore the 8-day composites were used to maximize the number of available data points for creating standardized surfaces. Composite images where more than 30% of cells contained no data were excluded from all subsequent analyses. Each composite image was standardized as:

$$MODIS_{STD,i} = (\bar{x}_i - x_{i,j}) / \sigma_i \quad (1)$$

where $\bar{x}_i$ and σ_i are the mean and standard deviation of image i , and $x_{i,j}$ is the LST value assigned at cell location j . The final standardized surfaces were generated by grouping images by month, removing outliers by excluding values falling outside of the 95% confidence interval at each cell location, and calculating the mean value at each cell location.

A number of predictor variables were excluded from the study, despite their common inclusion in correlative and mechanistic climate analyses. Distance to the coast (Daly *et al.*, 2007) was excluded due to a high correlation ($r=0.93$) with latitude and the use of standardized meteorological weather stations precluded the use of vegetation cover, slope, aspect and their interactions (Ashcroft and Gollan, 2012; Kearney *et al.*, 2014). Solar radiation metrics (direct and diffuse solar radiation, modelled ratio of solar radiation on a sloped surface to that of a flat surface accounting for terrain-dependent shading; Moore *et al.*, 1993; Böhner and Antonić, 2009; Nyman *et al.*, 2014) were initially considered as predictor variables; however, model coefficients demonstrated sign inconsistencies in several months, leading to their exclusion.

2.3. Data analysis

Predictions of daily maximum and minimum temperatures were obtained by interpolating anomalies derived from monthly climate normals in one 30 year reference period; 1981–2010. Climate normals were interpolated using partial bivariate splines (2DS), full and partial trivariate splines (3DS) and RK (Odeh *et al.*, 1995).

All kriging based analyses were performed in R (R Core Team, 2016) using the *gstat* package (Pebesma, 2004) and all spline-based analyses were performed with ANUSPLIN version 4.4 (Hutchinson and Xu, 2013). RK was implemented by first fitting regression models to the data points followed by ordinary kriging of model residuals. The final predictions at each location were calculated as the sum of the modelled value and the interpolated residual. Regression models were fit by generalized least squares using the *nlme* (Pinheiro *et al.*, 2015) package in R.

The smoothing parameter for spline interpolation was estimated by GCV using ANUSPLIN version 4.4 (Hutchinson and Xu, 2013). A semi-automated procedure for fitting variograms was used in all kriging analyses. Empirical variograms of regression residuals were calculated and initially fit to models using the *automap* package in R (Hiemstra *et al.*, 2009). The automated

fitting procedure optimizes variogram model parameters to minimize the residual sum of squares. The Gaussian, exponential, spherical and linear variogram models were all considered throughout the automated fitting procedure. The reliability of each variogram model was then assessed visually. In a small number of cases the fitting procedure was heavily influenced by semivariance in the initial distance bins, resulting in variograms with very short ranges. The parameters of these models were adjusted to provide a more consistent fit to the full empirical variogram.

Climate normals and daily anomalies were cross validated by iteratively removing one observation from the available data points and using it as a test location. Leave one out cross validation was chosen to ensure the most accurate representation of location-specific bias, and to minimize the effect of excluding novel observations. Climate normal model parameters were reassessed using the training dataset at each cross validation iteration. Variogram models were defined globally for each month during climate normal analysis to ensure a consistent and reliable model.

Model performance was assessed using the coefficient of determination (r^2), mean absolute error (MAE), root mean squared error (RMSE), ratio of the RMSE to the standard deviation of the observations (RSR) and mean error (BIAS). The RSR is a standardized model performance metric that is considered very good when < 0.5 and satisfactory when < 0.7 (Moriarty *et al.*, 2007).

2.4. Calculation and analysis of climate normals

Monthly climate normals require a sufficient number of observations to ensure a robust estimate of the long term mean; however, the length of available temperature records varies considerably throughout the Victorian weather station network. The inclusion of short term records can introduce biases and limit model performance if they are not representative of the normal period. Record length was extended using linear regression against nearby long term observations to minimize these biases, which has been shown to be effective in optimizing model performance for both temperature and precipitation climate normals (Hopkinson *et al.*, 2012).

For each month, weather stations with at least 20 years of daily observations were considered as long term records and used directly to calculate climate normals. These included on average 36% of the weather stations operating between 1981 and 2010. Weather stations with short to medium term records (5–20 years) were then regressed separately against the closest 5 weather stations with long term observations. Models were required to reach a significance level of 1% and have at least 4 years of overlapping observations to be considered further. Short to medium term records were then extended using the regression model returning the highest F score. This procedure allowed 85% of the weather stations operating between 1981 and 2010 to be included in the climate normal analysis. Short term records that did not meet the above criteria were only retained for the analysis of daily anomalies.

Climate normals were then interpolated using 2DS, 3DS and RK. Partial spline models were computed by including additional variables as independent covariates. All climate normal interpolations were performed using elevation as either an independent covariate (RK and 2DS) or spline variable (3DS). Elevation was expressed in kilometres for trivariate spline models in order to minimize interpolation error (Hutchinson, 1995; Hutchinson *et al.*, 2009). Standardized day time MODIS values were included as an independent covariate for maximum temperature. The topographic index of relative elevation and standardized night time MODIS values were included as additional independent covariates for minimum temperature.

2.5. Calculation and analysis of daily temperature

Daily predictions of maximum and minimum temperature were calculated by interpolating anomalies derived from the observed daily temperature and the monthly climate normal. Daily anomalies were calculated as:

$$\Delta Z_{m,t} = Z_{m,t} - \mu_m \quad (2)$$

where μ is the climate normal in month m , and Z is the observed value in observation period t . All anomalies were interpolated using bivariate splines. Cross validated daily temperatures were calculated as the sum of the predicted climate normal and the interpolated anomaly.

Interpolation variance at each target location was used to identify erroneous daily observations. Interpolated anomalies falling outside of 3.6 standard deviations of the observed anomaly were identified as suspect data points (Hutchinson and Xu, 2013). All suspect data points were excluded during daily cross validation and interpolation; however, they were retained for the purposes of calculating cross validation statistics to maintain conservative error estimates.

2.6. Analysis of temperature dependent bioclimatic variables

Variables such as mean annual temperature and mean diurnal range (Hijmans *et al.*, 2005) are commonly used in bioclimatic analyses (Elith and Franklin, 2013) and were therefore selected to assess the impact of including the topographic index and standardized MODIS values as predictors for temperature variables. Both variables were calculated using four alternate combinations of maximum temperature and minimum temperature models. The Victorian elevation-only climate dataset (VECD) was calculated using elevation as the only topographic predictor for both maximum temperature and minimum temperature. The Victorian topo-climate dataset (VTCD) builds upon the VECD with the addition of the topographic index as a predictor for minimum temperature. The Victorian elevation plus MODIS climate dataset (VECD + M) and the Victorian topo-climate plus MODIS dataset (VTCD + M) were calculated by including standardized day time MODIS values for maximum temperature and standardized night time MODIS values for minimum temperature as additional predictor variables. Further analysis of model performance was conducted by subtracting VECD values

from the VTCD, VECD + M and VTCD + M, and investigating the distribution of residual values.

2.7. Analysis of model behaviour across a topographically complex transect

Model performance in regions of complex topography were investigated further by extracting mean annual temperature, mean annual diurnal range and mean annual minimum temperature along a 7.75 km transect crossing two valleys. AWAP and WorldClim climate normals were also extracted to provide a comparison against the VECD, VTCD, VECD + M and VTCD + M datasets. The range and variability of extracted values were assessed using cross sections and boxplots.

3. Results

Cross validated error statistics for maximum and minimum temperature climate normals (1981–2010) are presented in Table 1. Trivariate splines had the lowest cross validation error for maximum temperature climate normals. Only marginal performance improvements to maximum temperature were obtained with the partial trivariate spline using standardized day time MODIS LST as an independent covariate. 2DS with elevation as an independent covariate provided a minor improvement over the full trivariate spline for minimum temperature climate normals. Including the topographic index of relative elevation as a covariate improved minimum temperature RMSE by

approximately 17% in comparison to the best performing elevation only model (2DS-E); however, only negligible differences were found between the partial bivariate spline and the partial trivariate spline. Partial trivariate splines provided the best interpolation performance for all minimum temperature climate normal models when using standardized night time MODIS LST as an independent covariate (34% improvement in RMSE for 3DS-M and 39% improvement in RMSE for 3DS-TM when compared against 2DS-E).

Empirical variograms of maximum temperature regression residuals (Figure 2) were fit using the Gaussian model from October to April and the exponential model from May to August. Including standardized day time MODIS LST in the regression component for maximum temperature climate normals reduced residual variance, particularly in the warmer months (October to March).

The exponential model was used exclusively to fit models to empirical variograms of minimum temperature regression residuals (Figure 3). The topographic index of relative elevation was effective in reducing residual variance, especially during cooler months (April to September) when compared against the elevation only model. Models using the standardized night time MODIS LST showed the lowest residual variance and shortest effective variogram ranges across all months. Despite these short effective ranges, the interpolated predictions consistently performed better than the regression component alone.

The monthly variability in RMSE for maximum and minimum temperature climate normals using a subset of the best performing models is illustrated in Figure 4. The addition of standardized day time MODIS values improves maximum temperature performance during the warmer months between October and April (1.4–11.2% reduction in RMSE). The relative performance of each minimum temperature climate normal model was consistent throughout the year, with the partial trivariate spline using standardized night time MODIS values and the topographic index providing the largest improvement in comparison to the partial bivariate spline (32.8–42.2% reduction in RMSE).

Cross validated error statistics for daily maximum temperature and daily minimum temperature are presented in Table 2. As with the climate normal analysis, daily anomalies performed best when using the MODIS corrected variants of the partial trivariate spline. A further improvement in minimum temperature performance was also achieved with the addition of the topographic index of relative elevation.

Spatial and temporal analyses of RMSE for all models shown in Table 2 are summarized in Appendices S1 and S2, Supporting information. Model performance tends to decrease in the eastern regions of Victoria, particularly in high elevation areas with low weather station density. Daily maximum temperature shows a seasonal trend in RMSE which is not reflected in the RSR, suggesting that this is due to increased temperatures rather than a decrease in interpolation accuracy during the summer

Table 1. Spatially and temporally pooled cross validated error statistics for mean monthly (1981–2010) maximum and minimum temperature interpolated using regression kriging (RK), bivariate splines (2DS) and trivariate splines (3DS).

	r^2	MAE	RMSE	RSR	BIAS
Maximum temperature (°C)					
<i>RK-E</i>	0.99	0.39	0.56	0.10	0.00
<i>RK-EM</i>	0.99	0.40	0.55	0.09	0.00
<i>2DS-E</i>	0.99	0.39	0.53	0.09	−0.01
<i>2DS-EM</i>	0.99	0.38	0.51	0.09	−0.01
3DS	0.99	0.36	0.51	0.09	0.00
3DS-M	0.99	0.35	0.48	0.08	−0.01
Minimum temperature (°C)					
<i>RK-E</i>	0.92	0.79	1.03	0.28	−0.01
<i>RK-ET</i>	0.95	0.64	0.83	0.22	−0.01
<i>RK-EM</i>	0.96	0.54	0.71	0.19	0.00
<i>RK-ETM</i>	0.97	0.52	0.67	0.18	0.00
2DS-E	0.93	0.74	0.96	0.26	−0.01
<i>2DS-ET</i>	0.95	0.62	0.80	0.22	−0.01
<i>2DS-EM</i>	0.97	0.50	0.66	0.18	−0.01
<i>2DS-ETM</i>	0.97	0.48	0.63	0.17	0.00
<i>3DS</i>	0.93	0.76	0.99	0.27	−0.03
3DS-T	0.95	0.62	0.80	0.22	−0.01
3DS-M	0.97	0.48	0.63	0.17	−0.01
3DS-TM	0.97	0.45	0.59	0.16	0.00

Combinations of elevation (E), topographic index (T) and standardized MODIS values (M) used as independent covariates are indicated in the model suffix. r^2 = coefficient of determination, MAE = mean absolute error, RMSE = root mean square error, RSR = ratio of the RMSE to the standard deviation of the observations, BIAS = mean error.

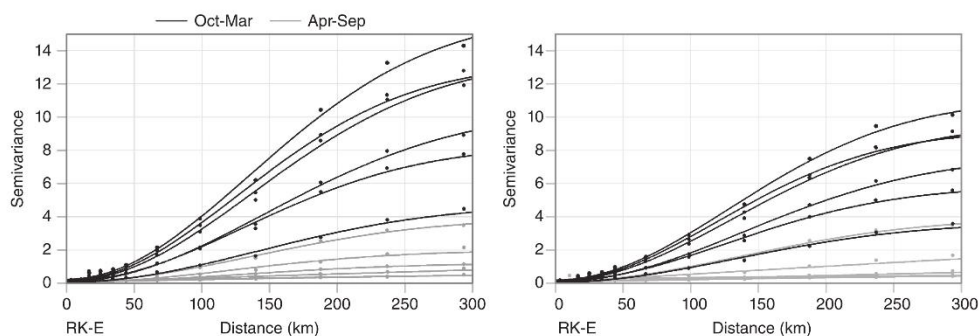


Figure 2. Monthly empirical and modelled variograms used for regression kriging of maximum temperature climate normals (1981–2010) using elevation (E) and standardized day time MODIS LST (M) as independent covariates.

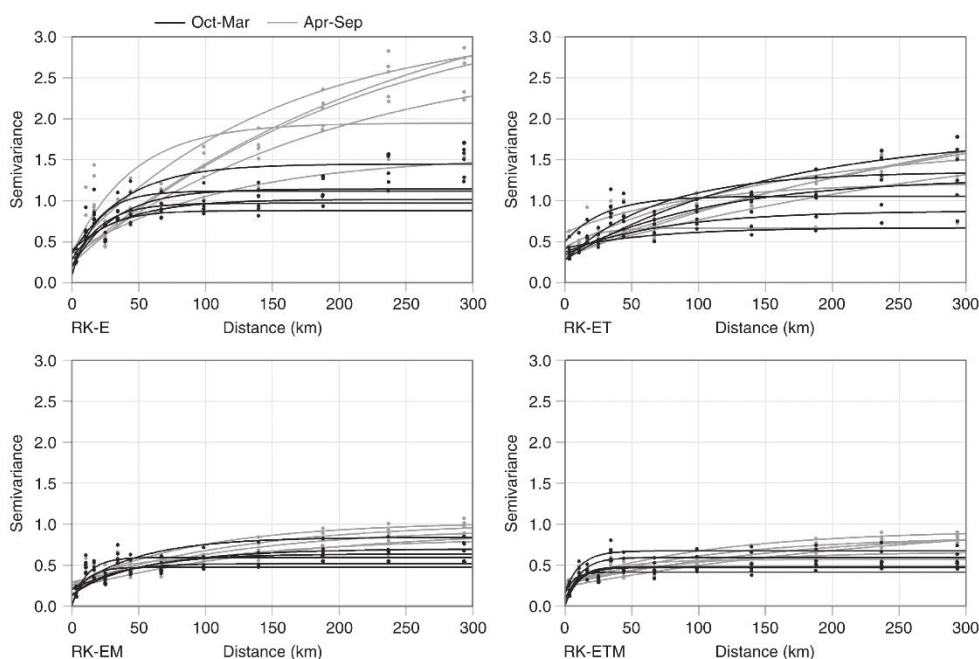


Figure 3. Monthly empirical and modelled variograms used for regression kriging of minimum temperature climate normals (1981–2010) using elevation (E), a topographic index (T) and standardized night time MODIS LST (M) as independent covariates.

months. Temporal variability in RMSE for minimum temperature does not appear to be seasonally dependent.

Mean annual temperature and mean annual diurnal range residuals, calculated by subtracting the VECD from the VTCD, VECD + M and VTCD + M, are illustrated in Appendix S3. All models using standardized MODIS values as covariates demonstrate the largest variability in residual values for both mean annual temperature and mean annual diurnal range. The VTCD mean annual temperature residuals range between -1.3°C and 1.8°C ,

compared with a range of -1.2°C to 2.4°C for the VECD + M and -1.5°C to 2.0°C for the VTCD + M. Mean annual diurnal range residuals range between -3.5°C and 2.7°C for the VTCD, compared with a range of -4.4°C to 2.9°C for the VECD + M and -3.6°C to 3.3°C for the VTCD + M.

The cumulative distribution of mean annual temperature and mean annual diurnal range residuals across Victoria are illustrated in Figure 5. Mean annual temperatures are lower than the elevation only model (VECD)

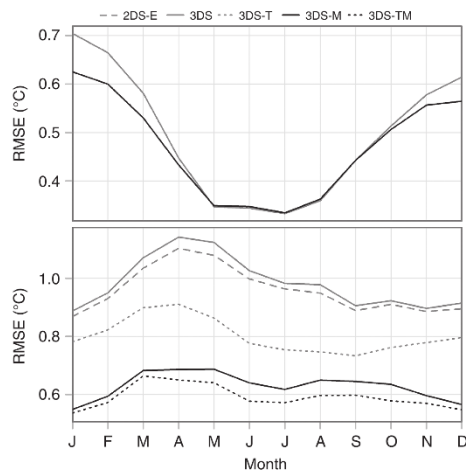


Figure 4. Cross validated RMSE of monthly climate normals (1981–2010) for maximum (top) and minimum (bottom) temperature using full trivariate splines (3DS), partial trivariate splines (3DS-T, 3DS-M, 3DS-TM) and partial bivariate splines (2DS-E). Elevation (E), topographic index (T) and standardized MODIS values (M) are used as independent covariates where indicated in the model suffix.

Table 2. Spatially and temporally pooled cross validated error statistics for daily maximum and minimum temperature anomalies (January 1981 to August 2014).

	r^2	MAE	RMSE	RSR	BIAS
Maximum temperature (°C)					
3DS	0.97	0.82	1.20	0.17	0.01
3DS-M	0.97	0.81	1.19	0.17	0.00
Minimum temperature (°C)					
2DS-E	0.87	1.34	1.81	0.36	0.04
2DS-ET	0.88	1.29	1.73	0.34	0.02
3DS	0.87	1.35	1.83	0.37	0.02
3DS-T	0.88	1.29	1.73	0.34	0.01
3DS-M	0.89	1.24	1.65	0.33	0.00
3DS-TM	0.89	1.22	1.63	0.33	0.00

Climate normals used to calculate anomalies are interpolated using bivariate splines (2DS) and trivariate splines (3DS) using combinations of elevation (E), topographic index (T) and standardized MODIS values (M) as independent covariates. r^2 = coefficient of determination, MAE = mean absolute error, RMSE = root mean square error, RSR = ratio of the RMSE to the standard deviation of the observations, BIAS = mean error.

in 58% of cells for the VTCD, and 65% of cells for both the VECD + M and VTCD + M. Mean annual diurnal ranges are higher than the elevation only model (VECD) in 58% of cells for the VTCD, 62% of cells for both the VECD + M and VTCD + M.

The transect illustrated in Figure 6 demonstrates model behaviour in topographically complex terrain for mean annual temperature, mean annual diurnal range and mean annual minimum temperature when calculated using the VECD, VTCD, VECD + M, VTCD + M, WorldClim and AWAP climate normals. Using the topographic index and

standardized MODIS LST values as covariates results in lower minimum temperatures predicted in valleys and higher values predicted on slopes. As a consequence of this behaviour, these models also predict broader diurnal ranges in valleys and narrower diurnal ranges on slopes. The trends observed for mean annual minimum temperature are reflected in mean annual temperature. WorldClim and AWAP climate normals demonstrate spatial homogenisation and reduced climatic variability when using coarser resolution data products.

Boxplots (Figure 7) illustrate the range and variability of values shown in Figure 6 for each dataset. Both the WorldClim and AWAP datasets result in very narrow diurnal ranges across the transect. This is not reflected in the VECD dataset and further highlights the impacts of coarser spatial scales across topographically complex terrain.

4. Discussion

The results of this study reaffirm that trivariate splines, which allow for a spatially varying dependence upon elevation, are robust for temperature interpolation (Hutchinson, 1995; New *et al.*, 2002; Hijmans *et al.*, 2005; Hutchinson *et al.*, 2009). Partial trivariate splines consistently performed well when using standardized MODIS LST values and the topographic index as independent covariates for minimum temperature. The magnitude of performance improvement suggests that these variables may be particularly useful for improving climatological surfaces; especially so considering that minimum temperatures form a component of many derived climate variables with ecological significance (i.e. vapour pressure deficit, potential evapotranspiration, aridity indices, bioclimatic variables). The benefits of using remote sensing data were much less pronounced for maximum temperature; however, an improvement was achieved during the warmer months. This is potentially due to the use of standardized meteorological weather stations and the scale at which maximum temperatures are altered by microclimatic conditions. The partial bivariate spline with a fixed dependence upon elevation; however, did perform slightly better than the full trivariate spline for minimum temperature. This is potentially due the spatial extent of the study which can lead to improved temperature interpolation when fixed lapse rates are used within a restricted area (Hutchinson *et al.*, 2009; Hutchinson and Xu, 2013). 2DS consistently performed better than RK, but only by a small margin. These methods can be expected to produce very similar results under optimal sampling conditions (Boer *et al.*, 2001). RK consistently outperformed the regression component alone, which suggests that the variogram models used were sufficient to characterize spatial dependence of regression residuals across the state.

The daily error statistics presented should be interpreted with caution as they may be biased towards point locations where there are a larger number of records. Several weather stations with long term records were among the poorest performing locations during cross validation.

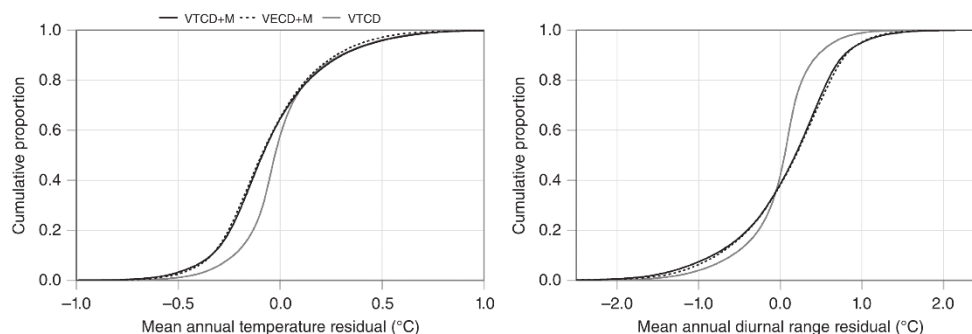


Figure 5. Cumulative distribution of mean annual temperature and mean annual diurnal range residuals throughout Victoria ($n = 3\,76\,834$), calculated by subtracting the Victorian elevation climate dataset (VECD) from the Victorian topo-climate dataset (VTCD), Victorian elevation plus MODIS dataset (VECD + M) and the Victorian topo-climate plus MODIS dataset (VTCD + M). Extreme values have been constrained for visual clarity.

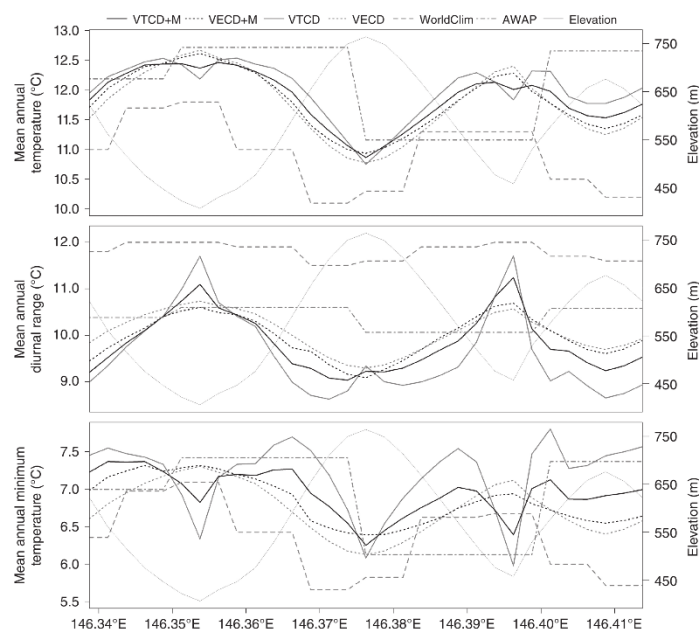


Figure 6. Mean annual temperature, mean annual diurnal range and mean annual minimum temperature across a transect (approximately 7.75 km) running west to east (146.339°–146.414°E, 37.741°S) across two valleys. Values calculated using the Victorian elevation climate dataset (VECD; 1981–2010; $n = 31$), Victorian topo-climate dataset (VTCD; 1981–2010; $n = 31$), Victorian elevation plus MODIS dataset (VECD + M; 1981–2010; $n = 31$), Victorian topo-climate plus MODIS dataset (VTCD + M; 1981–2010; $n = 31$), WorldClim dataset (1950–2000; $n = 10$) and AWAP dataset (1961–1990; $n = 4$).

For example, the Wilsons Promontory Lighthouse station (146.42°E, 39.13°S) consistently cross validated poorly across all methods, yet has a near complete observation record throughout the study period. When interpolating daily surfaces, it is highly likely that the prediction error at these locations would be much lower than the cross validated estimates. The magnitude of observed cross validation error is, however, within reasonable ranges when

assessed against previous Australian studies by Jeffrey *et al.* (2001) and Jones *et al.* (2009).

One of the key advantages of calibrating climate normal surfaces based on the existing weather station network is that anomaly interpolation can also be used to generate long term daily datasets without the need for post-processing or long-term field based observations. Furthermore, interpolation algorithms are able to identify and

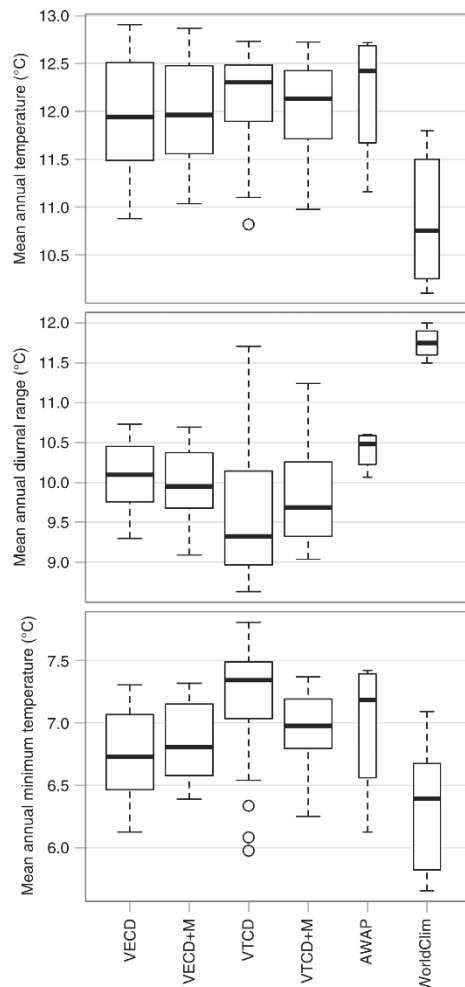


Figure 7. Boxplots of mean annual temperature, mean annual diurnal range and mean annual minimum temperature across a transect (approximately 7.75 km) running west to east (146.339°–146.414°E, 37.741°S) across two valleys. Values calculated using the Victorian elevation climate dataset (VECD; 1981–2010; $n = 31$), Victorian topo-climate dataset (VTCD; 1981–2010; $n = 31$), Victorian elevation plus MODIS dataset (VECD + M; 1981–2010; $n = 31$), Victorian topo-climate plus MODIS dataset (VTCD + M; 1981–2010; $n = 31$), WorldClim dataset (1950–2000; $n = 10$) and AWAP dataset (1961–1990; $n = 4$).

exclude suspect records and are not subject to spatial discontinuity that can arise when applying elevational lapse rates against the closest weather station observation. These daily surfaces are therefore suitable for use with process based models that require data with a high spatial and temporal resolution. For example, the TACA-GEM model used by Mok *et al.* (2012) to model tree species response to climate change and variability in south east Australia

requires daily data which limited the spatial resolution of analyses, requiring interpolation of model outcomes to finer scales. In addition, incorporating cold air drainage processes into daily datasets may be beneficial for process based microclimate models such as Niche Mapper (Kearney *et al.*, 2014) which are commonly run using coarse resolution daily temperature data that has been downscaled using elevational lapse rates.

The topographic index improved minimum temperature model performance over models that only used elevation as a predictor variable, which is consistent with previous studies by Daly *et al.* (2002, 2007) and Ashcroft and Gollan (2012) that have successfully used relative elevation metrics to characterize cold air drainage regimes at spatial scales ranging from 4 km to 25 m. Extracting spatial covariates at finer spatial resolutions (i.e. 25 m) is problematic without extensive field based observations, as the positional error of the existing Australian weather station network can in some cases be up to 1 km. Exploratory data analysis demonstrated consistent trends in model coefficients and the spatial variability of the topographic index was well represented by the weather station network, indicating that there were minimal detrimental effects to using the 250 m grid resolution for model calibration. The seasonal trends observed for relative elevation coefficients also suggest that a spatially varying dependence upon the topographic index may be advantageous at broader spatial extents and warrants further investigation. One of the core advantages of using a topographic index to improve temperature interpolation performance is that it is compatible with historical analysis in addition to climate change projections, unlike remotely sensed data that are characteristic of current conditions.

The use of standardized night time MODIS LST values demonstrated a large improvement in minimum temperature interpolation performance throughout Victoria. The incorporation of remote sensing data in this study was intentionally simple to ensure compatibility with the anomaly interpolation method and to minimize the effects of missing pixels, which is common in daily and 8-day composite MODIS LST surfaces for Victoria. Generating climate normals using standardized MODIS LST data comes with several advantages and limitations. This data indirectly captures microclimatic effects of land use such as those driven by vegetation cover and urbanization; however, these effects may be misrepresented in regions where anthropogenic or natural disturbance has occurred prior to and between 2000 and 2010. Standardized MODIS LST values therefore cannot be directly used to improve climate interpolation performance for historical data or projection of climate change scenarios due to the limitations imposed by continuous land use changes. The data are also somewhat limited by the relatively coarse resolution (approximately 1 km) of the LST product which is likely to introduce smoothing effects on prediction surfaces. Despite these limitations, minimum temperature climate normals cross validate well using MODIS data and may be useful for landscape scale research and applications such as modelling current species distributions, fire

weather forecasting, agricultural modelling and short term climate forecasts. MODIS calibrated prediction surfaces are also likely to be advantageous for studies conducted in regions where the landscape has remained relatively static over time.

The VTCD, VECD + M and VTCD + M datasets generated in this study demonstrate that the distribution of temperature is much more complex than can be captured by models that rely on elevation as the sole topographic predictor. This may be especially important for species with narrow bioclimatic envelopes or those predisposed to the understory, valleys, gullies or ridges, and also for the identification of climatic refugia. Transects and boxplots presented in Figures 6 and 7 demonstrate the importance of spatial scale in predicting temperatures across topographically complex terrain, particularly so considering the differences in variability when comparing increasingly coarse representations of diurnal range. The accuracy of bioclimatic variables that represent long-term mean conditions is critical as they are highly utilized in correlative analyses and for characterizing climatic conditions at field sites. Daily data also provides opportunities to quantify the severity and length of climate extremes and inter-annual variability. Incorporating extreme climate years or events can be critical for modelling the distributions of species (Zimmermann *et al.*, 2009). Fine scale daily data may provide opportunities to develop bioclimatic indices that are based on daily and/or monthly variability which cannot be captured by monthly long term conditions.

5. Conclusion

The existing historical weather station network in Victoria can be utilized to generate climate datasets of high spatial and temporal resolution that can characterize the effects of land use types and mesoscale processes such as cold air drainage which are influenced by local topographic complexity. Capturing fine scale topographic drivers of temperature will assist in bridging the gap between statistical interpolations and process based microclimate models without the need for post-processing. These temperature datasets may improve species distribution modelling, calculation of aridity and drought indices, and assessments of fire risk by incorporating the high degree of spatial variability in climate variables that exists in topographically complex landscapes but cannot be accounted for with methods that rely on elevational lapse rates alone.

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Supporting information

The following supporting information is available as part of the online article:

Appendix S1. Spatial and temporal analysis of daily maximum temperature cross validation statistics.

Appendix S2. Spatial and temporal analysis of daily minimum temperature cross validation statistics.

Appendix S3. Spatial distribution of mean annual temperature and mean annual diurnal range residuals obtained by subtracting the Victorian elevation climate dataset (VECD) from the Victorian topo-climate dataset (VTCD), Victorian elevation plus MODIS dataset (VECD+M) and the Victorian topo-climate plus MODIS dataset (VTCD+M).

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APPENDIX A.2: STEWART SB, CHODEN K, FEDRIGO M, ROXBURGH SH, KEENAN RJ, NITSCHKE CR. 2017. THE ROLE OF TOPOGRAPHY AND THE NORTH INDIAN MONSOON ON MEAN MONTHLY CLIMATE INTERPOLATION WITHIN THE HIMALAYAN KINGDOM OF BHUTAN. INTERNATIONAL JOURNAL OF CLIMATOLOGY 37(S1): 897–909. DOI: 10.1002/JOC.5045.

The role of topography and the north Indian monsoon on mean monthly climate interpolation within the Himalayan Kingdom of Bhutan

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ABSTRACT: Spatial climate datasets currently available for Bhutan are limited by weather station data availability, spatial resolution or interpolation methodology. This article presents new datasets for monthly maximum temperature, minimum temperature, precipitation and vapour pressure climate normals interpolated for the 1986–2015 reference period using trivariate smoothing splines. The inclusion of standardized day time Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) values as partial spline dependencies reduced cross validated root mean square error (RMSE) for maximum temperature by up to 16.0% and was most effective between March and September. Using both a topographic index of relative elevation and standardized night time MODIS LST values as partial spline dependencies reduced monthly mean minimum temperature RMSE by up to 23.4%. Neither variable was effective for minimum temperature interpolation between June and September. High humidity, extensive cloud cover and heavy precipitation occur during these months, which are likely to suppress the formation of temperature inversions that typically form under clear, calm conditions. These new temperature and precipitation surfaces show distinct differences from the WorldClim and CRU CL 2.0 datasets, which do not use weather stations within Bhutan for calibration. New precipitation surfaces better describe the heavy rainfall experienced in the southern foothills while retaining the effect of orography throughout the central valleys and ranges. The development of vapour pressure surfaces also allow for the calculation of ecologically important variables such as vapour pressure deficit, and may also be useful for solar radiation modelling in the region. The different datasets presented in this article will facilitate ecological and agricultural research in Bhutan and provide high quality surfaces needed for future climate change scenarios.

KEY WORDS Bhutan; Himalayas; monsoon; climate; splines; interpolation; MODIS; temperature inversion

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1. Introduction

The Himalayas comprise some of the most complex and extreme topography in the world, forming a natural barrier between the Tibetan plateau and the low-lying plains of the Indian subcontinent. The mountain range spans a distance of approximately 2400 km from west to east, reaching peaks of over 8500 m above sea level (asl) and crossing through Bhutan, India, Nepal, China and Pakistan. Uplift of the Himalayas and the Tibetan plateau over the past 50 million years has had large impacts upon the evolution of the Asian monsoon and intensified aridity in central Asia (Zhisheng *et al.*, 2001). Historically, the region has been of great interest to climatologists (Hill, 1881; Flohn, 1970; Barry, 2008); however, few studies have focused specifically on the climatology of Bhutan.

Bhutan has an extremely diverse climate given its small size, which is due to the highly variable and complex topographic features that comprise the landscape. The climate is expected to change considerably over the coming decades (Singh *et al.*, 2011) with mean annual temperature projected to increase by up to 3.5 °C and mean annual regional precipitation projected to increase between 80 and 180 mm by the 2050s (Tse-ring *et al.*, 2010). High resolution climate datasets can facilitate ecological and agricultural research and land management decisions, as the spatial distribution and productivity of vegetation is heavily dependent upon climatic conditions (Austin and Van Niel, 2011; Elith and Franklin, 2013). Currently there is a paucity of spatial climate datasets calibrated using ground-based station observations for Bhutan which limits the ability to conduct robust assessments of climate and climate change on forests and agricultural ecosystems.

The latitudinal position in addition to the topographic extremes and complexity of the Himalayan region means that the climate has some distinct features. Temperature

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lapse rates show clear trends that are associated with the seasonal reversal of the north Indian monsoon (Kattel *et al.*, 2013, 2015; Dorji *et al.*, 2016) and tend to be suppressed during the humid, cloudy and wet summer months. Increased levels of atmospheric moisture and the forced ascent of air against the Himalayas result in cloud formation, precipitation and an associated release of latent heat (Ohata *et al.*, 1981; Whiteman, 2000; Barry, 2008; Krishnamurti *et al.*, 2013), particularly at higher elevations (Kattel *et al.*, 2013). The cloudy conditions also cause more solar radiation to be reflected during the day, leading to cooler temperatures at lower elevations (Kattel *et al.*, 2013). Kattel *et al.* (2013) found residual errors were much larger for minimum temperatures than for maximum temperatures in Nepal and attribute this result to nocturnal temperature inversions. Temperature inversions typically develop under clear, calm conditions. At night time, thermal stratification of air in the lower troposphere (as a result of radiative cooling, subsidence, or convection of warm air over regions of cooler air) can cause a decoupling of the slope and valley atmospheres in mountainous terrain (Geiger, 1965; Whiteman, 2000; Barry, 2008; Daly *et al.*, 2009). As a consequence, cold air pools develop in basins and valley bottoms, and slopes become warmer due to convective processes. While this phenomenon is typically more pronounced in regions of complex topography, it may also manifest in comparatively flat terrain (Barry, 2008; Kattel *et al.*, 2013). Much weaker inversions are observed under windy conditions, or where cloud cover and water vapour decrease net longwave radiation losses (Iijima and Shinoda, 2000; Whiteman *et al.*, 2007; Zardi and Whiteman, 2013). The spatial distribution of minimum temperature is therefore heavily dependent upon local terrain, and several studies have demonstrated that focal topographic metrics (Daly *et al.*, 2007; Ashcroft and Gollan, 2012) and thermal remote sensing data (Stewart and Nitschke, 2016) can be effective for improving minimum temperature interpolation performance.

Globally consistent climatologies such as WorldClim (Hijmans *et al.*, 2005) and those developed by the Climatic Research Unit (CRU), University of East Anglia (New *et al.*, 1999, 2002; Harris *et al.*, 2014) can be used to extract climate data for most regions; however, they are somewhat limited for fine-scale ecological studies due to low spatial resolution and the variable density of suitable weather station data. The CRU suite of products are available at a spatial resolution of 18 or 50 km, and are therefore limited in their ability to resolve the effects of fine scale topographic complexity on climate. Downscaling approaches (e.g. Wang *et al.*, 2012) can be used to increase the spatial resolution of climate data; however, they typically rely on elevation dependencies and do not currently allow the incorporation of additional explanatory variables that can improve the quality of fine scale interpolations (Stewart and Nitschke, 2016). WorldClim was developed at a much higher spatial resolution of approximately 1 km but does not provide data on variables such as humidity, sunshine duration and wind speed that are important ecologically. One of the key challenges in developing

these globally representative surfaces is the availability of suitable station observations that are of sufficient density to capture regional scale climatological processes. Many regions of the world are underrepresented within these databases (CRU, 2016; National Oceanic and Atmospheric Administration (NOAA), 2016; Hijmans *et al.*, 2010), which can result in poor interpolation performance (Hijmans *et al.*, 2005). The networks of weather stations typically used for these analyses do not include locations within Bhutan (CRU, 2016; NOAA, 2016; Hijmans *et al.*, 2010). For example, the stations used for the WorldClim dataset (Figure 1; Hijmans *et al.*, 2010) are sparse given the topographic complexity in this region, and many of the weather stations are no longer operational, particularly in India near the southern border of Bhutan.

Until recently, the network of weather stations operating within Bhutan had not been used to develop spatially representative climate datasets for the region. Dorji *et al.* (2016) used linear and polynomial regressions to describe the distribution of seasonal temperature and precipitation across Bhutan. The equations developed by Dorji *et al.* (2016) are broadly representative of the region; however, they retain residual error when generating prediction surfaces and do not account for a spatially varying dependence upon elevation. Furthermore, extrapolating precipitation into the northern regions of Bhutan using polynomial regression and excluding the effects of orography are likely to lead to oversimplified predictions of rainfall.

The WorldClim and CRU CL 2.0 (New *et al.*, 2002) datasets have been generated using trivariate thin plate smoothing splines (Wahba, 1990) which are robust for climate interpolation (Hutchinson, 1995; Hutchinson *et al.*, 2009). Thin plate splines allow for a spatially varying dependence on elevation and minimize residual error at calibration locations; both of which are significant advantages over alternative methods such as linear regression. The thin plate spline algorithm is comprised of an affine component which is used to fit the global trend (as a function of spline variables) and a local non-affine component that adjusts the local nonlinear surface. Trivariate splines are most commonly fit with full spline dependence upon latitude, longitude and elevation. Additional independent covariates can be incorporated by extension to a partial spline model, which includes a parametric regression component (Bates *et al.*, 1987).

The objective of this study was to develop improved temperature, precipitation and vapour pressure datasets for Bhutan that address limitations of existing climate surfaces available for the region. This was done by using the local weather station network in conjunction with spline-based interpolation methods. The relative performance improvements that can be achieved by including thermal remote sensing data and local topographic metrics as partial spline dependencies when interpolating temperature variables were also assessed. These variables have recently demonstrated an improvement in temperature interpolation performance in topographically complex landscapes in southeast Australia (Stewart and Nitschke, 2016). The climate surfaces developed in this study were

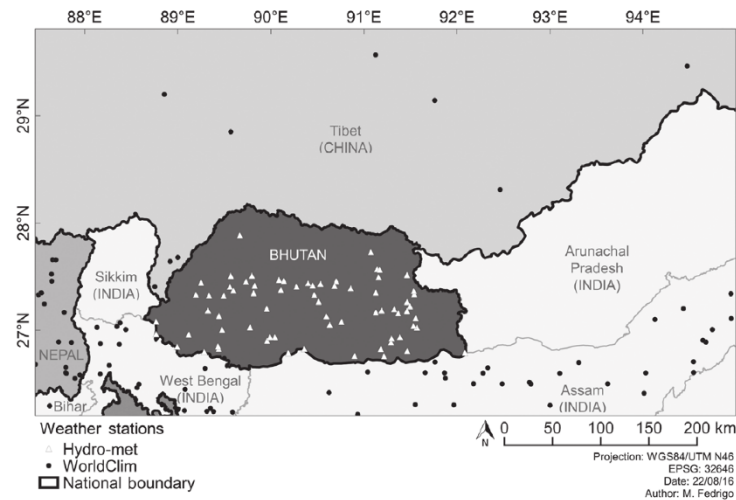


Figure 1. Weather stations used to generate climate surfaces for this study (1986–2015; Department of Hydro-Met Services) and the WorldClim dataset (1950–2000; Hijmans *et al.*, 2010).

compared against the globally representative WorldClim (Hijmans *et al.*, 2005) and CRU CL 2.0 (New *et al.*, 2002) datasets in order to highlight the importance of spatial resolution and observation density when developing interpolated climate surfaces.

2. Method

2.1. Study site

Bhutan is a land-locked country located on the southern slopes of the eastern Himalayas, sharing borders with China to the north and India to the east, west and south. The largely mountainous country is 38 394 km² in area and ranges from approximately 100 m asl in the south to 7500 m asl in the far north (Figure 2). The extreme range in elevation leads to highly variable climatic conditions within a distance spanning only 170 km in latitude (Norbu *et al.*, 2003). Like many regions of Asia the climate of Bhutan is monsoonal. South-westerly winds bring moist air from the Bay of Bengal to Bhutan during the summer phase of the north Indian monsoon (Krishnamurti *et al.*, 2013; Tamang, 2014). The country has three distinct climatic zones; alpine, temperate and subtropical (National Statistics Bureau (NSB), 2015). The climate is humid and subtropical in the southern plains and foothills (100–2000 m asl), with heavy rainfall occurring during the summer monsoon. The inner Himalayan valleys of the central regions have a temperate climate (2000–4000 m asl); however, they often receive less rainfall than the surrounding slopes and ridges as cloud cover and precipitation are suppressed by strong up-valley and up-slope winds (Whiteman, 2000; Barry, 2008). The high Himalayas to the north experience a cold alpine climate

(4000 m asl and above) and a permanent snow line can be found above 4800 m asl (Tamang, 2014). In winter, the snow line across the eastern Himalayas can descend to around 3000 m asl (Mani, 1981).

The estimated population of Bhutan is 784 000 (as of 2016), and approximately 56% of people are employed in the agricultural sector (NSB, 2015; UN Data, 2016). Over 70% of the country is under forest cover (Figure 3; Land Cover Mapping Project (LCMP), 2011; NASA LP DAAC, 2016). Bhutan hosts a diverse range of vegetation and forest types (Ohsawa, 1987; LCMP, 2011; National Biodiversity Strategies and Action Plan of Bhutan (NBSAP), 2014), owing to the complex topography and corresponding climatic variability. The subtropical climate zone is comprised of broadleaf, chir pine (*Pinus roxburghii*) and tropical lowland forest. Fir, mixed conifer, blue pine (*Pinus wallichiana*) and mixed broadleaf and conifer forest can be found in the temperate climate zone, and the alpine climate zone consists of meadows and scrubs.

2.2. Datasets

Daily maximum temperature, minimum temperature, precipitation and relative humidity records for 71 weather stations operating between January 1986 and December 2015 were obtained from the Department of Hydro-Met Services (DHMS), Ministry of Economic Affairs, Bhutan. Latitude, longitude and elevation at each station were extracted from site metadata also provided by the DHMS. The network of stations used throughout the analysis was distributed across elevations ranging from 180 to 3537 m asl (Figure 1). The record length at each station was on average 19.6 years long, with a minimum of 6.7 years and maximum of 30 years of observations. Daily records were excluded where the maximum temperature

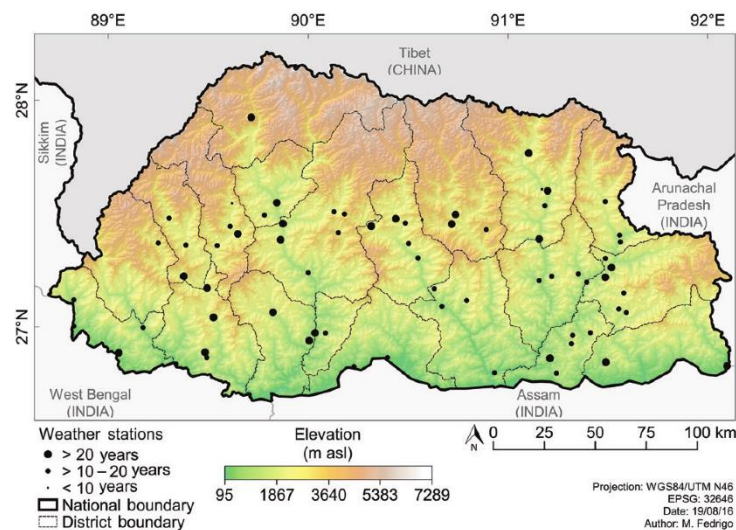


Figure 2. Digital elevation model of Bhutan (Jarvis *et al.*, 2008) and the weather station network operating between 1986 and 2015.

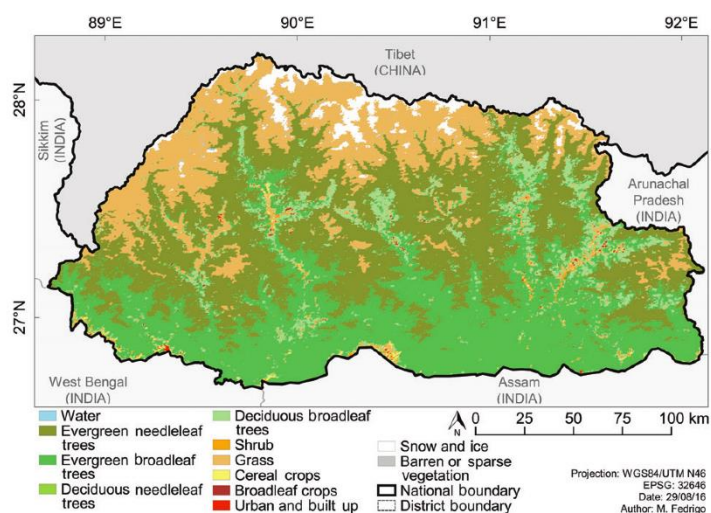


Figure 3. Dominant MCD12Q1 land cover classification (Friedl *et al.*, 2010; NASA LP DAAC, 2016) across Bhutan between 2000 and 2013 under the Plant Functional Type (PFT) scheme (Bonan *et al.*, 2002).

was reported as lower than the minimum temperature (795 daily records), relative humidity was below 0 or above 100% (128 daily records), or the amount of precipitation was negative (seven daily records).

Estimates of daily vapour pressure, rather than observations of relative humidity, were used to ensure dependence upon elevation. Daily vapour pressure was derived from the saturation vapour pressure of the mean daily temperature and relative humidity (Abtew and Melesse,

2013). The mean daily temperature was calculated as the average of the maximum and minimum temperature. The saturation vapour pressure, e_s , was calculated using a reparameterization (Alduchov and Eskridge, 1996) of the August-Roche-Magnus equation (Lawrence, 2005);

$$e_s(T) = 6.1094 \times \exp^{\frac{17.625 \times T}{243.04 + T}} \quad (1)$$

The daily vapour pressure, e , was then derived from the saturation vapour pressure at the mean temperature and

relative humidity (RH);

$$e = e_s(T_{\text{mean}}) \times \text{RH} \quad (2)$$

Provisional climate normals (hereafter referred to as climate normals), representing the mean monthly conditions between 1986 and 2015, were calculated for maximum temperature, minimum temperature, precipitation and vapour pressure at each station. Monthly values were computed using daily observations prior to the calculation of mean monthly values. Monthly precipitation was calculated as the sum of daily precipitation where observations were available for each day of the month. Monthly mean temperature and vapour pressure were calculated as the mean of each daily observation where the following criteria were met; (1) no more than 10 missing days of data were allowed, and (2) no more than 4 consecutive days of missing data were allowed (World Meteorological Organization (WMO), 2011). Calculating climate normals for any reference period may be biased due to short or incomplete records at different observation locations. A regression patching approach was tested to correct for any potential bias induced by short-term records by regressing observations against neighbouring stations (Hopkinson *et al.*, 2012; Stewart and Nitschke, 2016); however, this method did not produce reliable results. Monthly climate normals were therefore calculated for each station where at least 10 years of observations were available for each month (Hijmans *et al.*, 2005) to ensure interpolation was supported by a sufficient number of data points in different locations and at the highest elevations.

Potential biases in short-term means were investigated using interpolation variance and by analysing ranked residuals throughout the cross validation procedure for each variable. Stations were identified as suspect where the calculated mean value was >3.6 standard deviations from the cross validated prediction. This approach identified one suspect station which was subsequently removed from all analysis due to close proximity with neighbouring stations and short record length (10 years for each month). The removal of additional short-term records selected based on ranked residuals consistently led to decreased performance at neighbouring stations (including those with more than 20 years of data) and therefore they were retained throughout the analysis. Excluding the suspect station and those with less than 10 years of data resulted in a satisfactory spatial and temporal coverage, with the number of stations available for analysis reduced by between 6 and 11% for any variable or month.

The digital elevation model (DEM) used throughout the analysis was obtained from the CGIAR Consortium for Spatial Information (<http://srtm.csi.cgiar.org>). This was resampled to 7.5 arc s (approx. 225 m cell resolution at the equator) using the sink-filled 3 arc s (approx. 90 m cell resolution) Shuttle Radar Topography Mission (SRTM) dataset (Jarvis *et al.*, 2008). One of the issues with interpolating precipitation across a fine resolution DEM is that the predictions are heavily influenced by local topography, leading to unrealistically large differences at

very small spatial scales. As precipitation is not strongly correlated with elevation at distances up to 5 to 10 km (Hutchinson, 1998; Sharples *et al.*, 2005), the original DEM was smoothed using a Gaussian filter for calibrating and predicting precipitation (Barnes, 1964; Daly *et al.*, 2007). The use of a focal filter to smooth elevation allows for precipitation surfaces to be generated at high resolution without extreme short range variability. The degree of smoothing is determined by the filter extent and standard deviation of the Gaussian distribution. The smoothing filter was applied with a circular search diameter of 35 cells (approx. 7.8 km) and a standard deviation of 10 cells using the System for Automated Geoscientific Analysis (SAGA) software package (Conrad *et al.*, 2015). The required level of smoothing was determined by iteratively adjusting the standard deviation of the filter (5 to 25) and cross validating precipitation climate normals (Appendix S1). Performance was optimal at a standard deviation of 10 cells, although the differences between each level of smoothing varied by <1.5% in root mean square error (RMSE). Geographic coordinates were expressed in decimal degrees and elevation expressed in kilometres during all analyses (Hutchinson, 1995, 1998, 2009) to minimize error during cross validation and surface generation.

The effects of topographic position on minimum temperature were assessed using a topographic index of relative elevation, which has been shown to improve model performance by representing the effect of overnight temperature inversions and cold air pooling processes (Daly *et al.*, 2007; Ashcroft and Gollan, 2012; Stewart and Nitschke, 2016). This index was calculated as the square root of the difference between the elevation at each target cell and focal minimum within an 8.76 km circular search diameter. The optimal focal range for the topographic index was systematically assessed by iteratively adjusting the search diameter (1.1–90.2 km) and cross validating minimum temperature (Appendix S2).

Thermal remote sensing data from collection 6 of the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD11A2 (Wan *et al.*, 2015) Land Surface Temperature (LST) product (approx. 1 km cell resolution) was used as an independent covariate for temperature interpolation. The MOD11A2 MODIS product can be effective in improving temperature interpolation (Hengl *et al.*, 2012; Stewart and Nitschke, 2016) as it provides an indirect estimate of LST and is sensitive to land cover classification (Snyder *et al.*, 1998; Wan, 2006). All 8-day composite scenes available between February 2000 and December 2015 were downloaded using the MODIS package (Mattiuzzi, 2016) in R (R Core Team, 2016). Scenes were rejected where visual inspection indicated clear spatial artefacts, or the number of cells with invalid LSTs was >50% across Bhutan. This threshold was set to ensure enough scenes were retained during the summer monsoon, when there is a very high level of cloud cover. Each image was then transformed into z-scores, grouped by month and averaged for each cell location. Outliers falling outside of the 95% confidence interval were excluded when calculating the final mean value at each

cell location (Stewart and Nitschke, 2016). Standardized monthly MODIS surfaces were calculated separately for day scenes and night scenes to be used as predictors for interpolation of maximum temperature and minimum temperature, respectively. Owing to the extremely cloudy conditions and spatial artefacts noted for several months during visual inspection of the LSTs, clear sky masks from the MOD11A2 product were also used to support the analysis. Daily clear sky images were extracted by converting 8-bit integers in the 8-day composite clear sky data to binary vectors. The mean fraction of clear sky during the day and night was then calculated for each pixel, and as a regional average, for each month.

2.3. Data analysis

Monthly maximum temperature, minimum temperature, precipitation and vapour pressure climate normals for the 1986–2015 reference period were interpolated using trivariate splines (Wahba, 1990; Hutchinson, 1995) in ANUSPLIN 4.4 (Hutchinson and Xu, 2013). The spline smoothing parameter was estimated using generalized cross validation (GCV; Craven and Wahba, 1979). For each variable, full spline dependence upon latitude, longitude and elevation was assessed. Additional partial dependencies (Bates *et al.*, 1987) were also assessed for both maximum temperature (standardized MODIS day time LST) and minimum temperature (standardized MODIS night time LST, topographic index). The square root of vapour pressure (McKenney *et al.*, 2004) and precipitation (Hutchinson, 1995, 1998, 2009) climate normals were used for interpolation and the final predictions were subsequently converted back to units of hectopascals (hPa) and millimetres. ANUSPLIN internally corrects for the small amount of bias that arises as a result of these transformations (Hutchinson and Xu, 2013). As site elevations extracted from the smoothed precipitation DEM are a function of the surrounding landscape they may differ from values present in the site metadata (RMSE = 323 m). Precipitation was therefore cross validated using both the actual and smoothed elevation values to ensure the smoothed interpolation would produce reliable results.

Cross validation was performed by iteratively leaving out one observation and refitting the model until independent predictions were made for all locations. The coefficient of determination (r^2), mean absolute error (MAE), RMSE, ratio of the RMSE to the standard deviation of the observations (RSR; Moriasi *et al.*, 2007) and mean error (BIAS) were used to assess model performance. Following cross validation, monthly climate normal surfaces were generated using all available stations for each model.

Residual analyses were performed to investigate the differences in model predictions when using alternative variables for interpolation, and also to compare the surfaces generated in this study against globally representative climate datasets. In order to detect differences in the spatial distribution of model predictions for temperature, residual values were calculated for each partial trivariate spline model by subtracting the trivariate spline with full dependence upon latitude, longitude and elevation. Empirical

cumulative distribution plots were used to investigate the spread of mean annual maximum and minimum temperature residuals. November was selected to illustrate the spatial distribution of minimum temperature residuals.

Mean annual temperature and annual precipitation were extracted from the WorldClim (Hijmans *et al.*, 2005) and the CRU CL 2.0 (New *et al.*, 2002) datasets and compared against the new surfaces generated using the local weather station network. Residuals were calculated by subtracting the WorldClim and CRU surfaces from the gridded datasets generated in this study. Thermal remote sensing data is sensitive to land use type (Snyder *et al.*, 1998; Wan, 2006) and therefore partial spline models for temperature using standardized MODIS LST values were not assessed against the WorldClim or CRU datasets to ensure an appropriate comparison.

3. Results

Cross validated statistics for maximum temperature, minimum temperature, vapour pressure and precipitation climate normals are summarized in Table 1. All partial spline models for temperature variables provided a performance improvement over the full trivariate spline. Pooled statistics for maximum temperature demonstrate a 7.9% improvement in RMSE over the full trivariate spline when using standardized day time MODIS LST values as an independent covariate. Pooled statistics for minimum temperature demonstrate an improvement of between 10.4 and 12.3% in RMSE when using standardized night time MODIS LST values, the topographic index, or their combination, as independent covariates. The use

Table 1. Spatially and temporally pooled cross validated error statistics for mean monthly (1986–2015) maximum temperature, minimum temperature, precipitation and vapour pressure with ordinary and partial trivariate splines. Partial dependencies are indicated in the model suffix (*T* represents the topographic index; *M* represents standardized MODIS LST values).

	r^2	MAE	RMSE	RSR	BIAS
<i>Maximum temperature (°C)</i>					
3DS	0.93	1.15	1.44	0.26	0.03
3DS-M	0.94	1.09	1.33	0.24	0.01
<i>Minimum temperature (°C)</i>					
3DS	0.95	1.14	1.46	0.23	−0.02
3DS-T	0.96	1.04	1.31	0.20	0.00
3DS-M	0.96	1.03	1.28	0.20	0.00
3DS-TM	0.96	1.03	1.28	0.20	0.00
<i>Precipitation (mm)</i>					
3DS (site elevation)	0.89	0.25 ^a	0.47 ^a	0.34	−0.05 ^a
3DS (smoothed elevation)	0.90	0.22 ^b	0.43 ^b	0.30	−0.03 ^b
<i>Vapour pressure (hPa)</i>					
3DS	0.96	1.06	1.36	0.20	0.00

r^2 , coefficient of determination; RSR, ratio of the RMSE to the standard deviation of the observations; BIAS, mean error. ^aPrecipitation MAE (35.98 mm), RMSE (68.44 mm) and BIAS (−7.52 mm) expressed as a proportion of the mean. ^bPrecipitation MAE (32.41 mm), RMSE (62.40 mm) and BIAS (−5.01 mm) expressed as a proportion of the mean.

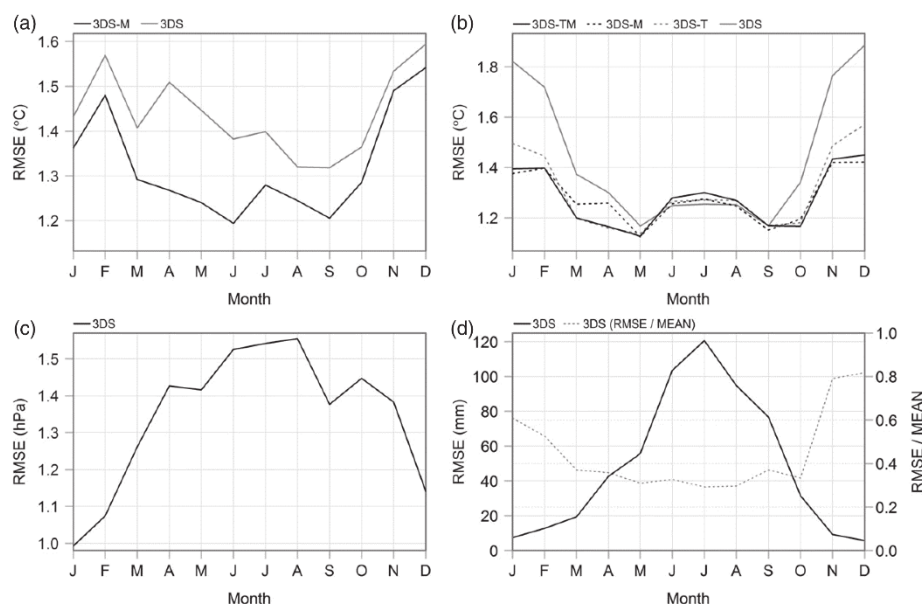


Figure 4. Cross validated RMSE of monthly climate normals (1986–2015) for maximum temperature (a), minimum temperature (b), vapour pressure (c) and precipitation (d) using ordinary trivariate splines (3DS) and partial trivariate splines (3DS-T, 3DS-M, 3DS-TM). The topographic index (T) and standardized MODIS values (M) are included as partial dependencies where indicated in the model suffix.

of smoothed DEM values rather than site elevations provided an 8.8% reduction in RMSE for precipitation. All variables achieved an RSR of 0.3 or less, indicating good model performance. Mean error (BIAS) was negligible for temperature and vapour pressure; however, there was a small negative bias for smoothed precipitation (-5.01 mm) which equated to -0.03% as a proportion of the mean observed value.

The cross validated monthly RMSE for all variables and models summarized in Table 1 are illustrated in Figure 4. The partial trivariate spline for maximum temperature (3DS-M) was effective throughout the year and demonstrated the largest improvement between January and October (4.8–16.0% reduction in RMSE) when compared against the full trivariate spline (3DS). Partial spline models for minimum temperature (3DS-T, 3DS-M and 3DS-TM) were most effective in improving performance during the cooler months between October and April; however, they also provided a small improvement in May. Minimum temperature typically performed best during this period when including partial dependence upon both the standardized MODIS values and the topographic index (3DS-TM; 10.4–23.4% reduction in RMSE when compared against 3DS). The RMSE of monthly precipitation climate normals cross validated using the full trivariate spline (3DS) was highest during the wettest months between May and September (RMSE between 55.8 and 120.7 mm). The ratio of the RMSE to the mean was relatively stable across this period (29.3–37.1%), suggesting

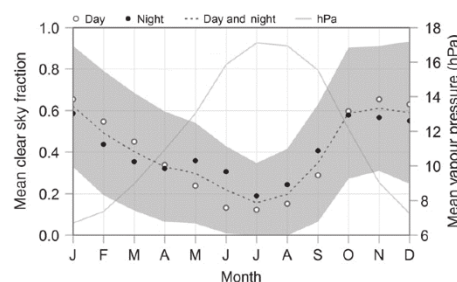


Figure 5. Regional monthly mean clear sky fraction (MOD11A2 clear sky days; Wan *et al.*, 2015) and vapour pressure. Confidence bands represent the mean clear sky fraction (day and night combined) ± 1 standard deviation.

that the high RMSE values are likely due to increased precipitation rather than reduced model performance.

Daily MODIS acquisitions show that the fraction of clear sky over Bhutan is lowest during the day between May and September (Figure 5). The regional mean vapour pressure is also highest during these months. With the exception of May, partial spline models were ineffective at improving minimum temperature interpolation performance throughout this period when compared against the trivariate spline with full dependence upon latitude, longitude and elevation. The clear sky fraction was on average lower during the night between October and April.

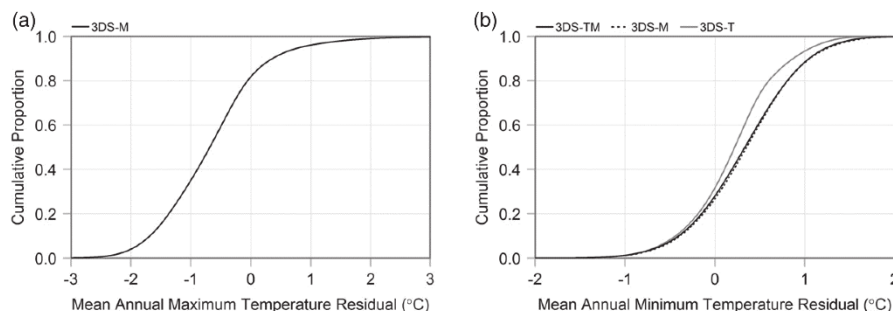


Figure 6. Cumulative distribution of mean annual maximum (a) and minimum (b) temperature residuals ($n = 814\,914$) calculated by subtracting the ordinary trivariate spline from model variants developed using partial dependencies. The topographic index (T) and standardized MODIS values (M) are used as partial dependencies where indicated in the model suffix. Extreme values are constrained for visual clarity.

The distribution of mean annual maximum and minimum temperature residuals, calculated by subtracting the full trivariate spline (3DS) from each partial trivariate spline variant (3DS-T, 3DS-M and 3DS-TM), are presented in Figure 6. Mean annual maximum temperature residuals (3DS-M) range from -4.2 to 4.8°C and are cooler than the full trivariate spline across 81.2% of the region. Mean annual minimum temperature residuals (Figure 6) demonstrate congruence between the partial trivariate spline models and are warmer across 68.2% of cells for 3DS-T (-2.2 – 1.9°C), 71.9% of cells for 3DS-M (-2.3 and 3.0°C), and 73.1% of cells for 3DS-TM (-2.1 and 2.6°C).

Minimum temperature residuals in November (Figure 7) show a similar spatial distribution for all models, with a warming of slopes and cooling of areas with low relative elevation. Minimum temperature interpolation using standardized MODIS LST values show a much broader range of values in comparison to variants using only topographic metrics. Residuals were up to 1.8°C cooler and 1.3°C warmer for 3DS-TM in comparison to the maximum range predicted by 3DS-T.

The spatial distribution of mean annual temperature and annual precipitation interpolated using the local weather station network (maximum temperature 3DS; minimum temperature 3DS-T; precipitation 3DS) show large deviations from the WorldClim and CRU CL 2.0 datasets (Figure 8). The regional mean annual temperature for locally calibrated interpolations was 0.75°C warmer than the WorldClim dataset, and 1.81°C warmer than the CRU dataset. This result was most pronounced across the western regions of Bhutan in the WorldClim dataset. For mean annual temperature, the residuals between the new surfaces and the WorldClim values varied by as much as 5.9°C and the residuals between the new surfaces and the CRU values varied by up to 12.9°C . The 3DS model predicts the greatest amount of precipitation across the southern foothills of Bhutan; however, unlike the WorldClim and CRU datasets, these high rainfall regions do not extend into the central valleys. Precipitation residuals show deviations of up to 3364 mm in the WorldClim dataset, and up to 2845 mm in

the CRU dataset when compared against locally calibrated interpolation. Precipitation typically decreases with elevation across Bhutan in the WorldClim and CRU datasets. The 3DS model exhibits an increase in precipitation with elevation across the central valleys and a decrease in overall precipitation towards the far north of Bhutan.

4. Discussion

The results of this study demonstrate the advantages of incorporating MODIS LST data and local topographic indices as additional partial dependencies when interpolating temperature variables across topographically complex landscapes, such as those in Bhutan. Stewart and Nitschke (2016) found similar outcomes for the effectiveness of these variables in southeast Australia, despite large differences in topographic and climatic conditions. They found that MODIS LST values improved maximum temperature interpolation performance the most during the warm summer months. In Bhutan, the largest improvements in maximum temperature interpolation performance were also achieved during the warmest months when using standardized MODIS LST values as an independent covariate. This performance improvement was maintained throughout the summer monsoon, despite heavy day time cloud cover which reduced the amount of data available to construct standardized surfaces. The MOD11A2 product is sensitive to land cover classification, and therefore, the seasonal performance differences may be due to the indirect detection of spatially aggregated microclimatic conditions responding to higher temperatures, particularly during the summer months.

Both the MODIS LST values and local topographic metrics were effective at improving minimum temperature interpolation performance during the dry months between October and May; however, neither provided a performance improvement between June and September. This congruence suggests that MODIS LST data may be particularly effective at detecting temperature inversion signals in the long-term climate record, and also indicates

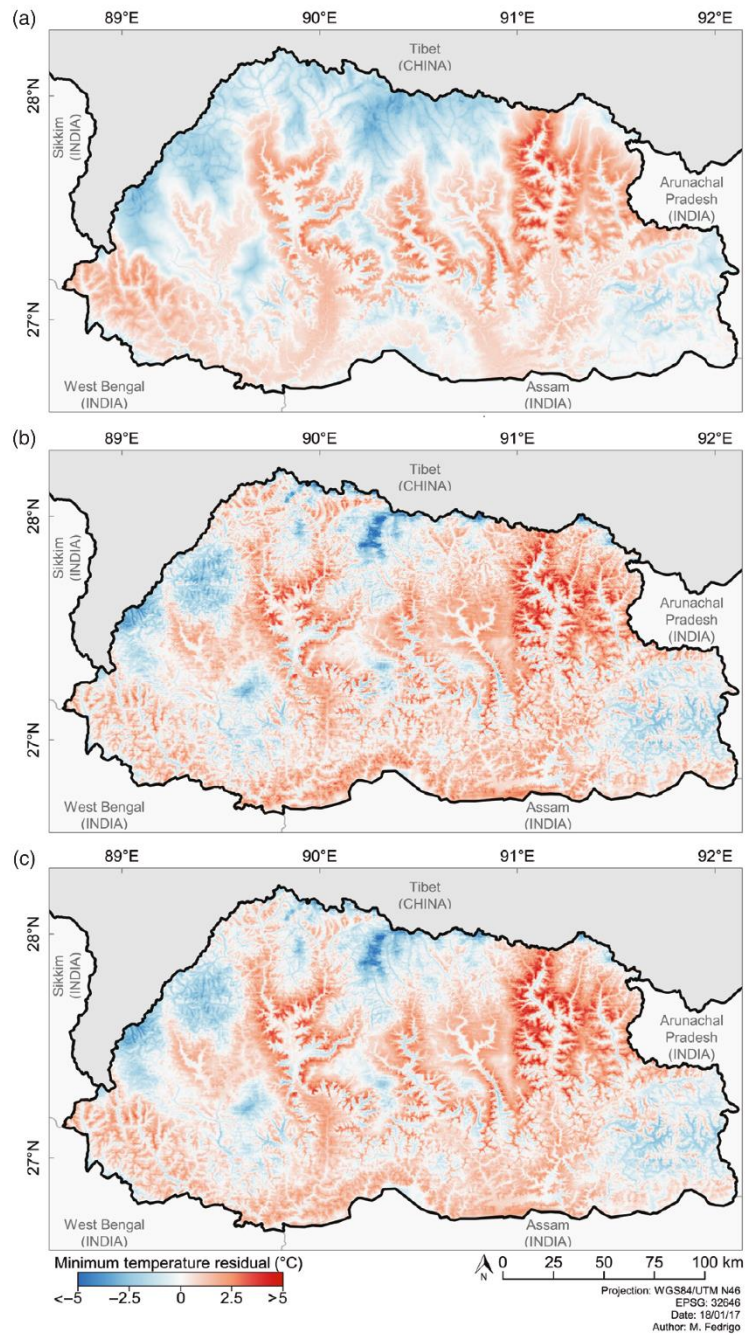


Figure 7. November minimum temperature residuals calculated by subtracting the ordinary trivariate spline (3DS) from trivariate splines with partial dependence upon the topographic index (a; 3DS-T), standardized day time MODIS values (b; 3DS-M), and both the topographic index and standardized day time MODIS values (c; 3DS-TM). Extreme residual values have been constrained for visual clarity.

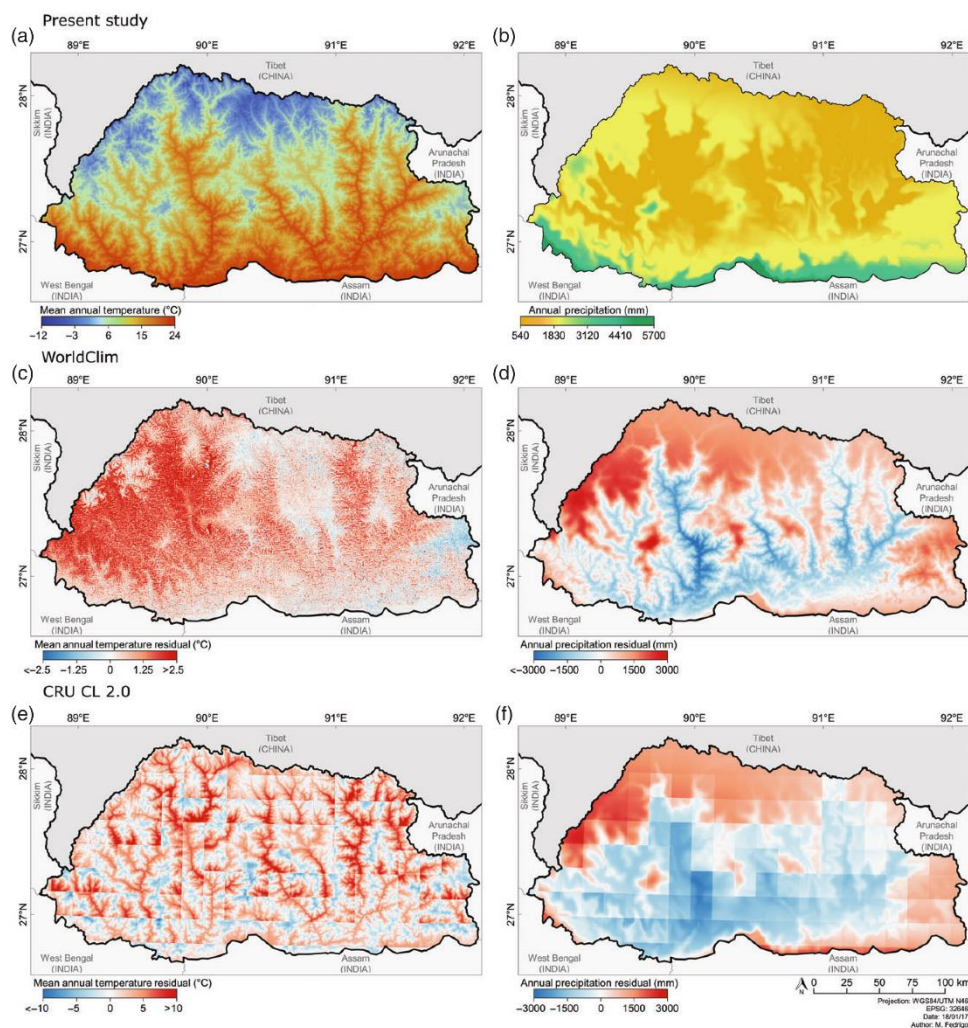


Figure 8. Mean annual temperature (a) and annual precipitation (b) calculated in the present study (full spline dependence upon latitude, longitude and elevation for maximum temperature and precipitation; additional partial dependence upon the topographic index for minimum temperature) and the spatial distribution of residuals when subtracting the WorldClim dataset (c, d; 1950–2000; Hijmans *et al.*, 2005) and the CRU CL 2.0 dataset (e, f; 1961–1990; New *et al.*, 2002). Extreme residual values have been constrained for visual clarity.

that the effectiveness of these variables may be considerably reduced during cloudy, wet and humid conditions that are characteristic of the summer monsoon in Bhutan. The extensive cloud cover observed during these months did not have a negative impact on maximum temperature performance when using MODIS LST values, and therefore the lack of performance improvement for minimum temperatures was likely due to the absence of a detectable inversion effect in the long-term record, rather than as a result of poor data quality. The release of latent heat

and suppression of outgoing longwave radiation associated with extensive cloud cover, heavy precipitation and high vapour pressure are likely to overcome the influence of temperature inversions and local topography during the wet months of the summer monsoon. These conditions are likely to suppress temperature inversion regimes due to their influence upon the surface energy balance (Iijima and Shinoda, 2000; Whiteman *et al.*, 2007; Barry, 2008; Zardi and Whiteman, 2013). The nocturnal release of latent heat has also been associated with the persistence of up-slope

and up-valley winds in the eastern Himalayas (Ohata *et al.*, 1981; Barry, 2008), which may further suppress thermal stratification of air near the surface and the development of cold air flows and pools. Both variables were, however, effective at improving minimum temperature interpolation performance between October and May. When included separately as partial dependencies, each variable led to a warming of slopes and a cooling of valley bottoms when compared against the trivariate spline with full dependence upon latitude, longitude and elevation. This result is consistent with the current understanding of nocturnal temperature distributions in mountainous terrain (Geiger, 1965; Whiteman, 2000; Barry, 2008).

Horizontal scaling of the topographic index resulted in an optimal search diameter of approximately 8.8 km, which is five times greater than the optimal diameter identified for southeast Australia (Stewart and Nitschke, 2016). Furthermore, using both MODIS LST data and the topographic index provided an additive improvement in minimum temperature performance in southeast Australia that was not found for Bhutan. This is potentially due to the scale of topographic variation in Bhutan (southeast Australia is comparatively much flatter with small peak-to-peak distances in the alpine regions) and the ability of the MODIS LST data to detect temperature inversions at appropriate scales. These results suggest that a spatially varying dependence upon the topographic index, calculated with short search diameters, in conjunction with MODIS LST data may allow for spatial interpolation of current minimum temperatures at much greater spatial extents. This may prove useful for spatial predictions of current climate; however, thermal remote sensing data is sensitive to land cover and therefore should not be used for projecting climate change scenarios.

When utilizing the local weather station network in Bhutan, new precipitation surfaces were able to characterize the heavy rainfall experienced in the southern foothills while retaining the effect of orography on precipitation throughout the central valleys and ranges. Precipitation is suppressed across the interior of these valleys and ranges by strong up-valley and up-slope winds (Whiteman, 2000), which can lead to an underestimation of rainfall throughout the central regions of Bhutan (Norbu *et al.*, 2003). Historical rainfall data and the distribution of vegetation suggests that the slopes and ridges throughout these regions are wetter than the inner valleys (Ohsawa, 1987; Norbu *et al.*, 2003), which is reflected in the spatial distribution of precipitation predicted in this study. The precipitation surfaces presented should be interpreted with a degree of caution, as much of the precipitation in the higher elevation regions of Bhutan falls as snow and elevations above 3537 masl are not represented by the local weather station network. Furthermore, precipitation is highly variable in the southern foothills of Bhutan and the representativeness of mean conditions is therefore dependent upon the available data series length.

The importance of spatial resolution and observation density is apparent when comparing the datasets developed

as part of this study against globally consistent climate datasets such as WorldClim and CRU CL 2.0. Analyses of the CRU CL 2.0 residuals show that the within-cell mean annual temperature variability can be as high as 20 °C for coarse resolution products in Bhutan. While downscaling approaches are an option, they cannot incorporate the effects of mesoscale processes such as temperature inversions. The temperature bias that is evident in the WorldClim residuals across western Bhutan, where temperatures are often at least 2.5 °C cooler than predicted in this study, indicate the importance of observation density and placement. It is unlikely that this region has experienced such an increase in mean annual temperature given that the datasets compared are centred on reference periods that differ by only 25 years. The analyses of precipitation residuals show extreme deviations between this study and both the WorldClim and CRU CL 2.0 datasets. These results support conclusions by Hijmans *et al.* (2005) that station density is perhaps the most important factor for inferring the quality of interpolated climate datasets. Station observations that qualify for inclusion in global databases may be limited in many cases due to data and weather station availability, insufficient length of records or lack of quality control processes. When globally representative surfaces such as WorldClim are used for regional studies, an evaluation of point density and topographic variability is recommended to evaluate whether or not these surfaces are likely to capture climatological processes at appropriate scales. Acquisition and interpolation of regional weather station data may be justified, and in some cases required, where the point density is too low.

The temperature and vapour pressure surfaces generated as part of this study allow for the spatial estimation of vapour pressure deficit and relative humidity. These variables can be critical for modelling vegetation distributions, as they characterize the atmospheric demand for moisture. While outside the scope of this study, vapour pressure surfaces may also be used for atmospheric attenuation when modelling potential incoming solar radiation (e.g. Böhner and Antonić, 2009; Conrad *et al.*, 2015). Vapour pressure precludes the need for estimates of lumped atmospheric transmittance, and allows for the effects of elevation to be incorporated into solar radiation predictions. Solar radiation modelling in Bhutan is, however, likely to be complicated by heavy cloud cover, particularly during the summer monsoon. Observations of sunlight hours are available at a small number of stations within the local weather station network in Bhutan, which may facilitate the production of high quality solar radiation surfaces in the future.

5. Conclusion

The datasets presented in this article provide a new resource for ecological and agricultural research in Bhutan. Alternative versions of temperature variables were generated to provide the highest quality surfaces (MODIS LST variants) and to maximize compatibility

with climate change projections (topographic index). These temperature datasets are calibrated specifically for Bhutan using the local weather station network, are sensitive to the climatic conditions present during the summer monsoon and incorporate inversion signals that cannot be detected using existing methodologies for statistical downscaling. Both the topographic index and the standardized night time MODIS LST values show evidence that they can detect the effects of temperature inversions on minimum temperature climate normals. These particular covariates are rarely used to improve temperature interpolation, and therefore their application is novel for the region. Precipitation surfaces characterize the heavy precipitation observed in the southern foothills, while retaining the effects of orography throughout the central regions of Bhutan. These effects are absent from global climate surfaces as they do not include weather station observations from within Bhutan. Incorporating the effect of orography on precipitation using trivariate spline interpolation provides a large improvement over polynomial regression techniques that have previously been applied in Bhutan. Globally representative humidity data is very coarse in resolution. The inclusion of vapour pressure surfaces allows for the calculation of humidity metrics and vapour pressure deficit, which will further facilitate ecological modelling and assist in decision making for climate change adaptation throughout Bhutan.

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Supporting information

The following supporting information is available as part of the online article:

Appendix S1. Calibration of precipitation digital elevation model.

Appendix S2. Calibration of topographic index for minimum temperature.

Figure S1. Spatially and temporally pooled cross validated RMSE for precipitation interpolated using varying Gaussian filter standard deviations (5–25) to smooth the DEM. **Figure S2.** Spatially and temporally cross-validated RMSE for minimum temperature interpolated using topographic search indices of varying search diameters (1.1–90.2 km). Standardized night time MODIS LST values (M) and the topographic index (T) are indicated in the model suffix where used as partial spline dependencies.

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