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 MODIS-LST; however, these have not been thoroughly tested to date. In this study, the relative benefits of including a localised topographic index and standardised 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 standardised night time MODIS LST values as covariates (34 – 39% reduction in RMSE). Standardised 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.

Keywords: climate, temperature, interpolation, kriging, splines, MODIS, topography, cold air drainage

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 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 (Xu & 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 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 mean monthly 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; Kutuwayo 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 (Xu & 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 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.

Method

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 – August 2014) there were 140 weather stations recording temperature across Victoria, with a mean minimum separation distance of 18.7 km.

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 2009; Nyman et al. 2014) were initially considered as predictor variables; however, model coefficients demonstrated sign inconsistencies in several months, leading to their exclusion.

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).

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.

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 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.

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.

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.

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 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).

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 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).

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 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 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).

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 summarised in Appendix S1 and S2 of the supplementary materials. 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 S3 of the supplementary materials. 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 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.

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 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.

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.

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 6 and Figure 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.

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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