Investigating the Relationship between Groundwater Depletion and Groundwater Dependent Agriculture on a Global Scale

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Abstract

The global food requirement has increased by 70% over the last century and the challenge of feeding an additional 2 billion people by 2030 is further intensifying the pressure on food production and irrigated agriculture. Consequently, stress on water resources is increasing, particularly on groundwater, which caters for about half of the global irrigation. Despite irrigated agriculture being the largest consumer of groundwater and a clear cause of groundwater depletion, quantitative knowledge about the link between these two is limited. In order to address this gap, this research investigates the relationship between groundwater depletion and groundwater dependent agriculture, particularly food production, at the global scale. After an introduction and detailed literature review, this research is presented in three parts: 1) developing a groundwater recharge model to estimate the global groundwater potential, 2) evaluating the current groundwater stress due to food production and 3) exploring future groundwater stress under different climate change scenarios.

Part 1 (Chapter 3) identified the most influential factors affecting diffuse groundwater recharge and developed an empirical model to estimate recharge at the global-scale. Recharge estimates reported in the literature from various parts of the world (715 sites) were compiled and used in model development and testing. Unlike conventional recharge estimates from water balance, a multi-model inference approach and information theory were used to select predictors and determine an empirical relationship between groundwater recharge and the most important predictors. Meteorological factors (precipitation and potential evapotranspiration) and vegetation factors (land use and land cover) were found to have the most predictive power for recharge estimation. The recharge model developed using the most influential factors was tested at different spatial scales and was applied globally at 0.5° resolution and annual timestep. The model showed acceptable performance in predicting long term groundwater recharge. At 97% of the testing sites the error in prediction ranged from -8 mm/y to 10 mm/y.
Having developed a model to estimate the global groundwater recharge, the current and future stress on the groundwater resources due to irrigated food production was investigated in Part 2 (Chapter 4) and Part 3 (Chapter 5). In Part 2, the stress on groundwater systems was analysed by calculating the ratio between groundwater use and availability, allowing for environmental baseflow requirements. The groundwater extraction potential or groundwater availability was determined using the recharge model developed in Part 1 and the irrigation water demand from a global soil water balance model, GlobWAT. Additionally, various pathways for stress reduction via improved irrigation efficiency and increased crop productivity were explored in this part. From this study, it was found that of 63 countries utilizing groundwater for irrigation, one third of them are overexploiting groundwater resources, while the groundwater in one-fifth of them is moderately to heavily stressed. Moreover, the groundwater stress is mostly focused on a few of the heavily populated areas including the North China Plain, North-west India and Central USA. About 450 million tonnes of global annual food production is produced from non-renewable groundwater exploitation. Increases in irrigation efficiency and irrigation productivity were found to be effective in reducing but not eliminating groundwater stress without compromising food security under current population. By increasing the global irrigation efficiency to 90%, groundwater stress in the most severely affected areas could be reduced by 40%. The improved efficiency would also mean that additional food could be produced from the part of groundwater sustainably extracted. Additionally, improved irrigation productivity (increasing the food produced per unit of water extracted) in conjunction with increased irrigation efficiency could reduce the current level of unsustainable food production by three quarters.

Part 3 (Chapter 5) investigates the future status of groundwater resources and associated unsustainable food production under climate change. The climate change impact on groundwater resources was investigated by forcing the groundwater recharge model developed in Part 1 and the GlobWAT irrigation demand model with HadGEM2-ES General Circulation Model (GCM) outputs from phase 5 of the Coupled Model Intercomparison Project (CMIP5). The analysis was done from 2006 to 2100 for Representative
Concentration Pathways (RCP) 4.5 and 8.5. This chapter followed the same methods used in Chapter 4 with the future climate data. It was found that both irrigation water requirement met from groundwater (+7%) and the groundwater available for extraction (+3%) would increase in the future under these scenarios. The gap between the water demand and water availability increases, leading to greater stress on groundwater resources globally. Under future food demand, by 2080, 25% (RCP 4.5) and 29% (RCP 8.5) of the total food produced from groundwater would have to be met by overusing the groundwater resources. Regional variability in these global trends was also explored.

The results from this thesis give key insights into the dynamics of irrigation stress on groundwater systems and identify hotspots of groundwater stress across the globe. This information is crucial to evidence-based management of groundwater and also to meeting the needs of current and future populations.
Declaration

This is to certify that:

1. this thesis comprises only my original work towards the degree of Doctor of Philosophy,
2. due acknowledgement has been made in the text to all other material used,
3. the thesis is fewer than 100,000 words in length exclusive of tables, maps, bibliographies and appendices.

Chinchu Mohan
Melbourne, November 2019
Preface

All the work presented in this thesis is original and was conducted by the candidate during her Ph.D. candidature from 2015 to 2019. This research was supervised by Prof. Andrew William Western from the University of Melbourne, Assoc. Prof. Yongping Wei from the University of Queensland and Prof. Madan Kumar Jha from the Indian Institute of Technology, Kharagpur.

A list of publications produced based on the study are given below.

JOURNAL


• Chinchu Mohan, Andrew Western, Yongping Wei and Madan K Jha, Global Assessment of Groundwater Stress from Irrigated Food Production, Global Environmental Change Journal (submitted-under review).

• Chinchu Mohan, Andrew Western, Yongping Wei and Madan K Jha, Climate change impact on global groundwater stress and associated food production (to be submitted to Nature Climate Change).

CONFERENCE


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I owe my greatest gratitude to my mother, my brother and my entire family for their motivation and support during my PhD. I am equally grateful to my partner Sujai Ramachandran for being an excellent friend and critic and walking on this journey with me and believing in me even in the hardest times.

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Chapter 1

Introduction

1.1 Background of research

Groundwater is the largest liquid freshwater reserve on the planet. It caters for the drinking water demand of approximately 3 billion people as well as being a major source of irrigation water. Globally 38% of the total irrigated area is equipped for irrigation with groundwater [Siebert et al., 2010]. Groundwater, which once served as a temporary option during dry seasons, has become the primary option, especially in the surface water-limited areas. Due of its year-round availability and no requirement for large-scale infrastructure like major dams and canals, groundwater irrigation is an attractive choice for farmers particularly in developing countries. Annually, 982 km$^3$ of groundwater is withdrawn globally for various purposes, of which 70% is for irrigation [NGWA, 2016].

In the last 100 years the world population has quadrupled, from 1.7 billion in 1900 to more than 7.3 billion in 2014, and is expected to continue to grow significantly in the future [Gerland et al., 2014]. This dramatic increase in population has led to increased food requirements, intensifying the pressure on all the resources required for food production. The foremost effect was seen on water resources, with a greater proportion of food production being from irrigation and a six-fold increase in water extraction. This has resulted in the over exploitation of both surface and groundwater resources, including the depletion of 21 of the world’s 37 major aquifers [Richey et al., 2015]. Furthermore, climate change had also accelerated groundwater depletion [Richard G Taylor et al., 2013]. Groundwater depletion threatens human lives and livelihoods in many ways, ranging from critical reduction in water availability to natural disasters such as land subsidence [Chaussard et al., 2014; Ortiz-Zamora and Ortega-Guerrero, 2010; Phien-Wej et al., 2006; Sreng et al., 2009]. Increasing pumping depth had also resulted in the mining of fossil groundwater which hardly get replenished with natural deep percolation.
Despite groundwater depletion being evident and irrigated food production being the dominant cause of it, the assessment of stress on the groundwater systems due to irrigated agriculture is often neglected [Dalin et al., 2017]. Moreover, our knowledge of the relationship between the two is very limited, which compromises our ability to manage water resources sustainably. Information about the interplay between food production and groundwater depletion is also crucial to manage the needs of the future population growth under changing climate. In order to fill this gap, this study was undertaken to evaluate the impact of irrigated food production on groundwater resources in the present and in the future.

1.2 Research objectives and questions

A detailed literature review of relevant knowledge is provided in Chapter 2 but first the research questions and the overall structure of the thesis are introduced in the remainder of this introductory chapter. The overall objective of this study is to investigate the relationship between groundwater depletion and groundwater dependent food production at a global scale. This overall objective will be addressed by answering three interdependent research questions described below:

**Objective 1** (Research question 1): How can groundwater recharge be modelled at a global scale considering all the major controlling factors?

This Objective is to identify the factors governing groundwater recharge at a global scale and develop an empirical model using the most influential factors to estimate diffuse rainfall recharge. This objective also includes the creation of a ground-based groundwater recharge validation dataset across the globe.

**Objective 2** (Research question 2): What is the relationship between groundwater depletion and groundwater dependent food production at the global scale?

This Objective is to investigate the impact of groundwater irrigated food production on global groundwater systems. Specifically, I evaluate the stress on groundwater in the past
three decades and quantify the unsustainable food production globally. The stress will be evaluated by considering water demand for irrigation and the water available for sustainable extraction, which will be estimated using the model developed in Objective 1. Potential pathways for stress reduction without compromising food security will be explored via improving irrigation efficiency and water productivity.

**Objective 3** (Research question 3): What is the potential impact of changing climate on groundwater depletion and groundwater dependent food production?

This Objective is to investigate the role of climate change in groundwater depletion due to irrigated food production. This objective integrates the concept of stress introduced in Objective 2 with the climate change scenarios. It attempts to predict the fate of groundwater systems in next 100 years under different climate change scenarios. The trends in sustainable food production over the next 100 years are also estimated.

The structure of the PhD thesis and interdependency of research questions are shown in Figure 1.1. The three questions correspond to three results chapters.

![Figure 1.1 Conceptual map showing order and dependency of research questions.](image-url)
1.3 Thesis overview

The thesis is structured into six chapters to address the objectives presented in section 1.2. This chapter provides a general introduction to the thesis topic and structure, which is followed by a comprehensive literature review in Chapter 2 supporting the objectives and research questions defined in Chapter 1. Chapters 3 through 5 are the results chapters corresponding to each of the three main objectives. These are included in journal publication format. Each result chapter has individual research objectives which map back to the main objective of the thesis. Each also contains a separate literature review supporting the question that the chapter addresses and a detailed methodology. Finally, in Chapter 6, an overall synthesis and discussion of the results from the three research questions is included. This chapter also includes the contributions, limitations and future scope of this study. The following paragraphs give a more detailed outline of each of the following chapters.

Chapter 2 presents the literature relevant to the objectives of this study. It reviews the common methods used to estimate groundwater recharge and their major limitations. Later in this chapter various developments over time in estimating the stress on the water resources due to a wide range of factors was discussed. Specifically, the effect of food production was reviewed in detail. This is followed by a compilation of current state of knowledge on climate change impact on groundwater resources. At the end of this chapter a list of perceived research gaps and their link to the proposed research questions is included.

Chapter 3 presents the results for research question 1, along with the methodology adopted to address it. This chapter is a journal article published in Hydrology and Earth System Sciences (https://doi.org/10.5194/hess-22-2689-2018). An empirical global groundwater recharge model was developed to estimate the water available for extraction. In order to develop this model, groundwater recharge data from 715 points all over the world, ranging from 1981 to 2014 were compiled from the literature. Unlike conventional recharge estimation, this study used a multi-model inference approach and information theory to select predictors, develop a relationship between groundwater recharge and major
influencing factors, and to predict groundwater recharge at 0.5° resolution. The results from this section of research showed that meteorological factors (precipitation and potential evapotranspiration) and vegetation factors (land use and land cover) had the most predictive power for diffuse recharge.

Chapter 4 focuses on research question 2. This chapter is under review in Global Environmental Change journal. This chapter details the evaluation of stress induced on groundwater by irrigated food production. The stress was estimated as a ratio of irrigation water demand to groundwater available for extraction. The demand was estimated using a global water balance model called GlobWAT and irrigation efficiency from FAO and the water availability was estimated using the recharge model developed in Chapter 3. This part of the study also accounts for environmental water requirements. The results from this chapter give key insights into the dynamics of irrigation stress on groundwater systems and the potential from the improvements of both irrigation efficiency and crop water productivity to address the sustainability of groundwater use.

Chapter 5: This chapter describes objective 3 in the form of a journal article to be submitted to Nature Climate Change. The effect of climate change on groundwater and groundwater dependent agriculture is investigated in detail in this chapter. This chapter takes the analysis in Chapter 4 a step forward by incorporating the climate change effects. In this chapter, the potential changes in groundwater stress and unsustainable food production over the next 80 years are investigated under two different climate scenarios viz., (Representative Concentration Pathway) RCP 4.5 and RCP 8.5. The results from this chapter are the identified potential hotspots on groundwater stress due to food production and the food production challenge under future changing climate.

Chapter 6 synthesizes and discusses the results obtained in Chapters 3 to 5. It sets out key limitations and future research directions before finally summarizing the overall conclusions derived from the study.
Chapter 2

Literature Review

This chapter aims to review the research from previous studies investigating groundwater stress and its relationship with irrigated food production. It is structured in five sections with three main sections (section 2 to 4) reviewing the existing state of knowledge and knowledge gaps which lead to the three research questions addressed in this thesis. Section 2.1 gives a general overview of global groundwater resources and its role in food production. Section 2.2 reviews literature on large-scale groundwater recharge estimation, which is one of the major factors determining the groundwater potential of an area. This section provides the background knowledge required in formulating Research Question 1. Then the current state of global groundwater depletion and future responses of groundwater to climate change are reviewed in section 2.3 and 2.4 respectively. Section 2.3 and 2.4 aided in formulating Research Question 2 and 3 respectively. Finally, the knowledge gaps are summarized in section 2.5.

2.1 Global groundwater resources and groundwater dependent food production

2.1.1 Global groundwater resources

Groundwater is a vast almost ubiquitous source of relatively high-quality water [Richard G. Taylor et al., 2012]. The lower vulnerability to pollution and year-round accessibility in relatively low cost have increased the popularity of groundwater resources. Groundwater resources have played a vital role in uplifting the economy of many arid and semi-arid regions. Large increases in agricultural production have resulted, and millions of people globally have benefited, from exploiting groundwater resources. Currently, a third of the total global fresh water withdrawal is from groundwater resources [Döll et al., 2012]. In the last decade, 36%, 42% and 27% of the total domestic, agricultural and industrial water needs
have been met from groundwater resources respectively [Döll et al., 2012]. In most European countries, more than 70% of the total water consumption is met from groundwater. Moreover, globally, a third of irrigated land is irrigated with groundwater [Shiklomanov, 1998]. Groundwater has played a critical role in the agricultural boom in developing countries like India during the Green Revolution [Repetto, 1994]. The importance of groundwater is not just limited to meeting various demands. Groundwater also reduces the stress in geological deposits and over extraction leads to land subsidence. Groundwater also absorbs minor seismic shocks, preventing them reaching the land surface [Holzer, 1979; Kundu et al., 2015].

A major issue is that groundwater resources are often mis-conceptualized as an inexhaustible resource, which has led to their overexploitation [Edmunds, 2004; Llamas and Martínez-Santos, 2005]. This groundwater overexploitation leads to the depletion of the resource, affecting hydrological and human systems in complex ways either directly or indirectly. It can threaten human lives in a wide range of ways, ranging from reduction in available water for survival [Jackson et al., 2001] to natural disasters like groundwater subsidence [Galloway and Burbey, 2011] and landslides [Allis et al., 2009; Chaussard et al., 2014]. A detailed discussion of the causes and consequences of groundwater depletion is provided in Section 2.3.

Despite being a crucial natural resource, which is being increasingly studied, our overall understanding of groundwater resources is very limited. Specifically, the lack of reliable data is a major constraint for groundwater studies at all scales, particularly for large scale studies.

2.1.2 Large scale groundwater data: status and uncertainties

The limited availability of groundwater data at global, regional or basin scale is always very challenging. One of the first attempts to estimate the global groundwater resources was in 1960 by a currently non-functional group in United Nations (UN) [United Nations, 1960]. Following this study there was extensive debate around whether a global estimate of
groundwater was necessary for groundwater management, as most of the groundwater uses and issues were highly localized. However, due to the increased need for transboundary groundwater governance and policies and increase in the extent of groundwater use, the need for large scale groundwater information became well accepted. In later years, Shiklomanov [1998] and the FAO’s AQUASTAT database (http://www.fao.org/nr/water/aquastat/main/index.stm) estimated the global water resource, of which groundwater was a component. Recently, various works have aimed to numerically quantify the groundwater resource and map the global major aquifers and their recharge patterns. The World-wide Hydrological Mapping and Assessment Program (WHYMAP) is such an effort to map the major recharge areas and their characteristics (http://www.whymap.org/). Large scale estimation of groundwater recharge is detailed in Section 2.2. The International Groundwater Resource Assessment Centre (IGRAC) also compiled available regional groundwater data [IGRAC, 2018].

Both the IGRAC and FAO statistics were based on estimates compiled from national and subnational institutions. The data estimation and reporting capacities of national agencies vary significantly, which raises concerns about the accuracy of the data [Kohli and Frenken, 2015]. In addition, according to the FAO AQUASTAT reports, most national institutions in developing countries prioritize subnational level statistics over national level statistics, and in most cases, data are not available for all subnational entities. This decreases the accuracy of country wide averages and raises concerns about their reliability as standard measures. The recently rapid increases in groundwater use in some regions of Asia are significantly under reported [Giordano, 2009]. Recent survey shows that groundwater irrigation use in India [T Shah et al., 2004] and China [J Wang et al., 2006] is ~40% greater than the AQUASTAT data. Thus, there are significant uncertainties in global statistics of use and availability. Due to the constrains and uncertainties of these data, the importance and state of groundwater resources are not fully understood or appreciated.
2.1.3 The role of groundwater in global food production

Groundwater resources play an important role in global food production. Expansion of irrigated agriculture has had a substantial impact on food production globally. Irrigation played a pivotal role in agricultural booms in many countries such as India and China during the green revolution of the 1960s-70s. According to Repetto [1994], “The Green Revolution has often been called a wheat revolution; it might also be called a tube well revolution”. Groundwater, once a temporary source for irrigation during dry seasons, has now become the primary source in many regions, especially in water-limited areas. Year-round availability and minimal infrastructure requirements make groundwater irrigation an attractive choice for farmers. Global annual groundwater extraction is 982 km$^3$; 70% of which is for irrigation [NGWA, 2016]. Crop yield and irrigation efficiency are generally higher in groundwater irrigated areas than those with canal irrigation [Meinzen-Dick, 1996; T Shah et al., 2000]. In heavily populated countries like China and Mexico, more than half of the irrigation requirement is met from groundwater resources [Dains and Pawar, 1987; Jinxia Wang et al., 2007]. Whereas in India, more than 80% of the total agricultural production is from groundwater [Dains and Pawar, 1987]. Groundwater also acts as a buffer for agriculture during extreme events such as drought when rainfall and surface water resources are insufficient. Agro-economic stability in California was maintained by switching to groundwater during the early 1990s drought [Gleick and Nash, 1991]. Despite all the benefits of groundwater irrigation, excessive use and poor management has led to serious degradation of groundwater in both quantity and quality.

Stress on the groundwater systems due to agriculture is a very complex phenomenon and its relationship with food production at various scales remains highly uncertain. Given the dependence of agriculture on groundwater and the stress on surface water resources [Konikow, 2011], it is clear that reduction in groundwater availability will have adverse effects on food production. However, few quantitative estimates of this inter-relationship have been made. In addition, the lack of high-quality international datasets discretising the yield from different irrigation sources makes the quantification of the relationship between groundwater stress and groundwater dependent food production notoriously difficult. This
is one of the prime motivations for this study. In order to study the stress on the groundwater systems, knowledge on how much water is going into the system as recharge and how much groundwater is taken out of the system to meet the demands is essential.

2.2 Large-scale groundwater recharge modelling

Groundwater recharge is one of the most important factors for sustainable groundwater withdrawal and, together with groundwater outflows, well yield and quality considerations, determines the development potential of an area [Döll and Flörke, 2005b]. Groundwater recharge connects the atmospheric, surface and subsurface components of the water balance and is sensitive to both climatic and anthropogenic factors and also other factors like vegetation, soils, topography and hydrogeology [Gurdak, 2008; Herrera-Pantoja and Hiscock, 2008b; Holman et al., 2009; Jyrkama and Sykes, 2007]. At local to basin scales, various studies have employed different methods to estimate groundwater recharge including tracer methods, water table fluctuation methods, lysimeter methods, and simple water balance techniques. Some of these studies input recharge to numerical groundwater models or dynamically link it to hydrological models to estimate variations in groundwater storage under different climate and land cover conditions [Aguilera and Murillo, 2009; Ali et al., 2012; Herrera-Pantoja and Hiscock, 2008b; Sanford, 2002]. One important requirement for predicting groundwater recharge is to understand the factors influencing it.

2.2.1 Factors influencing groundwater recharge

The factors controlling groundwater recharge can be broadly divided into three groups; 1) climatic/meteorological factors, 2) topographic factors and 3) geologic factors [Winter, 2001]. Climate, particularly rainfall influences the water available for recharge. Topographic factors like surface relief determines how much water infiltrates into the soil and finally the deeper geologic settings provides the permeability for the infiltrated water to reach the deeper aquifers [Sanford, 2002]. The weighted control of various factors on recharge varies from region to region. For example, in relatively arid or high relief regions, climate factors have more control over recharge. On the other hand, in humid or low relief
regions, geological factors determine the recharge rate. Generally, in humid regions, recharge occurs in topographic highs whereas in arid or semi-arid regions occurs mainly in topographic lows [Scanlon et al., 2002]. Numerous studies have found precipitation to be a major factor influencing recharge. For example, in south-western USA, 80% of recharge variation is explained by mean annual precipitation [Keese et al., 2005b]. However, the influence of meteorological factors on groundwater recharge is highly site specific [Döll and Flörke, 2005b]. The effect of meteorological factors can also depend on whether the season or year is wet or dry, type of aquifer and irrigation intensity [Adegoke et al., 2003; Moore and Rojstaczer, 2002a; Niu et al., 2007].

In addition to the aforementioned factors, vegetation also controls the amount of recharge into the groundwater systems. Vegetation has a high correlation with other physical variables such as soil moisture, runoff capacity and porosity, which adds to its recharge explanatory power [Kim and Jackson, 2012]. Recharge is greater in barren areas than areas with vegetation and it is much lower in regions with deep rooted trees [Gee and Hillel, 1988]. Allison et al. [1990] reported that, recharge in certain regions of Australia doubled when the native Eucalyptus trees were replaced with shallow rooted vegetation. Even though we have a fair knowledge of climate and vegetation controls on recharge, our understanding about other factors influence on recharge at a larger scale is still vague. As groundwater recharge is the key factor determining the extraction potential of groundwater systems, scientific understanding of recharge at a larger scale is crucial in evaluating the stress on the system.

2.2.2 Groundwater recharge estimation

There are numerous techniques to quantify groundwater recharge. The best choice of the method is highly dependent on the overall objective and spatial/temporal scale.

2.2.2.1 Ground-based measurement techniques

The various ground-based groundwater recharge estimation techniques can be broadly divided into unsaturated zone techniques and saturated zone techniques [Scanlon et al.,
The unsaturated zone techniques are applicable in semi-arid or arid regions where the unsaturated zones are thick [Gee and Hillel, 1988; Hendrickx and Walker, 1997; Scanlon and Goldsmith, 1997; Zhang and Walker, 1998]. Generally, the recharge in this zone is estimated by considering the drainage rates, in other words, these methods estimate the potential recharge. Lysimeters [Brutsaert, 2013; Young et al., 1996] and zero flux planes [L Richards et al., 1956] are two of the most popular physical techniques used in the unsaturated zone to estimate the water budget. Apart from these, natural or artificial chemical or isotopic tracer techniques are used to estimate recharge in the unsaturated zone. Bromide, $^3$H, and visible dyes are some of the commonly used tracers to estimate recharge [Aebly, 1998; Athavale and Rangarajan, 1988; Flury et al., 1994; Kung, 1990]. One disadvantage of unsaturated zone methods is that they are not well suited for estimating recharge over large areas. In such situations, saturated zone methods come in handy. Unlike unsaturated zone methods, saturated zone methods estimate the actual recharge to the aquifer. Water table fluctuation method [Hall and Risser, 1993; Rasmussen and Andreasen, 1959], Darcy’s law [Belan and Matlock, 1973; Theis, 1937], tracer techniques like bomb-pulse tritium ($^3$H) [Egboka et al., 1983; Robertson and Cherry, 1989], chlorofluorocarbons (CFCs), tritium/helium-3 ($^3$H/$^3$He) and chloride mass-balance (CMB) [Eriksson and Khunakasem, 1969] methods are the most commonly used saturated zone techniques to estimate actual groundwater recharge.

In humid regions, the groundwater recharge is often estimated by quantifying the baseflow. However, the adequacy of using this technique is highly dependent on how, when and where the flow gauging is done, and the adequacy of hydrograph separation techniques used to estimate baseflow. Several studies have reported variations of two orders magnitude in recharge estimates depending on the method used for estimating base flow [Bullock et al., 1997; Tallaksen, 1995]. Even though the ground-based techniques can accurately measure the recharge to groundwater systems, it requires a large number of measurements to make an acceptable recharge estimate over a large region. This makes it almost impossible to solely use these techniques to estimate recharge at regional scales or above.
2.2.2.2 Remote Sensing Information

Remote sensing products provide an opportunity to estimate hydrological components at a very large spatial extent. However, conventionally most remote sensing products measure the surface components of the landscape and/or hydrological cycle. Given the data availability, aerial photography and visible and near-infrared satellite observations have been used to study groundwater resources by exploiting the link between the surface and subsurface components [Schmugge et al., 2002; Schultz and Engman, 2012; Waters et al., 1990]. These methods are not very accurate in groundwater resource due to the indirect nature of the link between the observations and groundwater [Jha et al., 2007]. In the late 1980s, microwave remote sensing was applied to study groundwater resources. Microwave remote sensing can provide direct soil moisture measurements in the top few centimetres of soil. However, it is difficult to link the microwave remote sensing measurements to soil moisture at depth, let alone groundwater recharge [Jackson et al., 2001].

Another remote sensing approach uses gravity fluctuations. Since the start of Gravity Recovery and Climate Experiment (GRACE) mission in 2002, the use of remotely sensed products, groundwater studies had gained a new momentum [Rodell et al., 2009]. The gravity anomalies from GRACE allow us to estimate variations in total water storage for the first time. The GRACE measurements are relatively coarse monthly data with a spatial resolution of 1° i.e., roughly 111 km at equator, which limits it application to large basins. GRACE observations have been well validated with ground-based observations from various major groundwater basins all over the world [J Famiglietti et al., 2011; Feng et al., 2013; Scanlon et al., 2012; Voss et al., 2013]. However, the use of GRACE data is not well suited for small scale studies as the adjacent grid cells of the GRACE products share information with each other.

2.2.2.3 Hydrological models

Unlike surface water in streams, lakes and reservoirs, groundwater resources are not concentrated in small areas. Therefore, due to its spatial variability, a high number of
measurements is required to make a realistic estimate of the recharge over a sizable area [Döll and Fiedler, 2007]. This is expensive and often infeasible in many cases. Modelling groundwater recharge using different techniques provides a tractable approach to tackle this problem. Modelling of recharge mainly focuses on either the unsaturated or saturated zone. Unsaturated zone recharge is generally modelled using watershed models where the recharge is calculated as a residual term in the water budget [Arnold et al., 2000; Hatton, 1998; Leavesley et al., 1995]. Watershed models can be lumped, giving single value for the entire area of interest, or can be spatially distributed. With advances in the computational capability, new methods have been used to estimate unsaturated recharge using long-term simulations. Numerical solution of Richards equation is one of the most widely used approach of this type [L A Richards, 1931]. Several models including HYDRUS [Simunek et al., 1996], VS2DT [Lappala et al., 1987] and BREATHE [Stothoff, 1995] use Richards equation to model drainage from the unsaturated zone, which is assumed to represent groundwater recharge. The application of Richards equation models is mostly restricted to smaller areas due to its high level of complexity and data requirements.

Recharge estimation using groundwater models became more widely applicable with the development of inverse modelling techniques. In inverse modelling technique, a nonlinear algorithm is used to find the best fit between observations and modelled outputs and also produces the sensitivity of observations to the model parameters [Cooley, 1977; Yeh, 1986]. By the end of 20th century, many studies used inverse modelling to estimate the total groundwater recharge [Flint et al., 2002; Franssen et al., 2009; Karlsen et al., 2012; EP Poeter and Hill, 1997]. None of these studies have distinguished the recharge based on source. Hashemi et al. [2013] first used inverse groundwater modelling to quantify the natural and artificial recharge in south Iran. In their study, Hashemi et al. [2013] developed a conceptual 3D finite difference approach and employed it using MODFLOW 2000. Recently, a joint inversion combining groundwater age and heads has further expanded the ranges of approaches for inverse modelling of recharge [Portniaguine and Solomon, 1998; Reilly et al., 1994].
2.2.2.4 Empirical models

An alternative way for estimating recharge without involving water-budget equations is using empirical models. The empirical models aid the average recharge estimates of an area based on point observations. They are also used to estimate the parameter values for a hydrological model. These models are generally an equation defining recharge as a function of climatic, topographic and/or lithologic factors. The most popular empirical recharge model represents recharge as a function of precipitation [Keese et al., 2005a; Maxey and Eakin, 1949]. The fraction of the effective precipitation into groundwater recharge depends on several factors with the water table being the most influential one [Healy, 2010]. Regression techniques are also employed in hydrologic studies to extrapolate recharge estimates in space and time using independent parameters [Cherkauer and Ansari, 2005; Gebert et al., 2007; Holtschlag, 1997]. Despite they are very effective in the recharge estimates, the regression techniques and empirical models often require a number of recharge measurements and usually get biased due to uncertainties in the data.

2.2.3 Large-scale recharge studies

In the last few decades, interest in global-scale recharge analysis has increased for various scientific and political reasons [Tögl, 2010]. Increasing interest in global effects like climate change and its resulting impact on recharge is one of the major driving forces triggering global scale investigations. Macro-scale modelling of the terrestrial hydrologic cycle has been done either by integrating land surface models with atmospheric models [Koirala et al., 2012b; Nijssen et al., 2001; Pokhrel et al., 2015] or by using stand-alone hydrologic models [Alcamo et al., 2003; Van Beek and Bierkens, 2009]. L’vovich [1979] made the first attempt to estimate large-scale groundwater recharge by creating a global recharge map using baseflow derived from river discharge hydrographs. After L’vovich [1979] until the early 21st century, there was little research on large-scale groundwater recharge apart from country-level compilations of statistics by international organizations such as the Food and Agricultural organization (FAO) and the Water Resource Institute (WRI).
In the early 2000s, several researchers have attempted to model global groundwater recharge using different global hydrological models and global-scale land surface models [Koirala et al., 2012a; Scanlon et al., 2006a; Wada et al., 2010]. The next large scale groundwater recharge estimate was done by Döll [2002] who modelled global groundwater recharge at a spatial resolution of 0.5° using the WaterGAP Global Hydrological model (WGHM) [Alcamo et al., 2003; Döll, 2002]. In this study, runoff was divided into fast surface runoff, slow subsurface runoff and recharge using a heuristic approach. This approach considered relief, soil texture, hydrogeology and occurrence of permafrost and glaciers for the runoff partitioning. However, the WaterGAP failed to reliably estimate recharge in semi-arid regions [Döll, 2002]. WGHM overestimated recharge by 10 to 20% in semi-arid and arid regions. Later in 2007, WGHM was re-tuned against 1235 gauging stations to adjust its bias in semi-arid and arid regions [Döll and Fiedler, 2007]. However, in this study, there was no consideration of the influence of vegetation which has been reported to be the second most important determinant of recharge by many researchers [Jackson et al., 2001; Kim and Jackson, 2012; Scanlon et al., 2005].

Several global hydrological models including PCR-GLOBWB [Biemans et al., 2009; Van Beek and Bierkens, 2009] and MATSIRO (Takata et al., 2003) have also been developed with improved groundwater representation. In the PCR GLOBWB model, surface discharge and storage are modelled using the kinematic wave approximation and first order linear reservoir approach, respectively. PCR-GLOBWB, was versatile enough to represent sub-grid variability by separating short and tall vegetation [Wada et al., 2010]. In most of the first-generation global hydrological models, base flow runoff was represented as free gravity drainage, ignoring transport towards and through groundwater systems. This inadequate representation led to bias in the estimation of groundwater recharge. In most large-scale models, recharge was considered to be a fixed fraction of total runoff. One model, Minimal Advanced Treatments of Surface Integration and runoff (MATSIRO) used a dynamic representation of groundwater using an unconfined aquifer model with two-way interactions. This model is capable of varying the storage capacity of underlying aquifers with every time step based on the previous time step simulation [Koirala et al., 2012b]. This enables
MATSIRO to model the two-way interaction between saturated and unsaturated zones. Mean global recharge estimates by different large-scale hydrological models are shown in Table 2.1.

Table 2.1 Global groundwater recharge estimates from different global models

<table>
<thead>
<tr>
<th>Reference</th>
<th>Global groundwater recharge (km$^3$/y)</th>
<th>Model used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Döll [2002]</td>
<td>13826</td>
<td>WaterGAP</td>
</tr>
<tr>
<td>Scanlon et al. [2006b]</td>
<td>13090</td>
<td>Country statistics</td>
</tr>
<tr>
<td>Wada et al. [2010]</td>
<td>15200</td>
<td>PCR-GLOBWB</td>
</tr>
<tr>
<td>Koirala et al. [2012b]</td>
<td>29900</td>
<td>MATSIRO</td>
</tr>
</tbody>
</table>

These large-scale recharge estimates give insights into the groundwater extraction potential at a global scale. Mapping recharge using global hydrological models enables the research community to estimate global groundwater depletion for the first time. However, much uncertainty exists in the relationship between groundwater recharge and various governing factors including meteorological factors, lithological factors, topographic factors and vegetation factors. Moreover, large-scale hydrological models generally consider recharge as a generic fraction of runoff. These estimates are not very reliable due to the lack of explicit consideration of factors discussed in section 2.2.1.

2.3 Global groundwater depletion and stress analysis

2.3.1 Global groundwater depletion (GWD)

In the last 100 years, there has been a fourfold growth in world population, from 1.7 billion in 1900 to more than 7.3 billion in 2014 [Gerland et al., 2014]. In order to support the food requirements and associated economic development of the growing population, global water withdrawal has increased by nearly 6 times over the last century. Seventy percent of this increased water withdrawal was for meeting agricultural demand [Wada et al., 2010]. This increase in the exploitation of groundwater and surface water resources across the globe was most pronounced after the mid-20th century [Siegfried et al., 2009]. Global statistics indicate
that groundwater resources are being progressively depleted. The increasing demand for freshwater has resulted in overexploitation to such a level that the future availability of freshwater sufficient to sustain life is in question. Increasing demand has resulted in decreasing per capita water availability, and it is estimated that over 35% of the world population is currently under severe water stress [Kummu et al., 2010].

Since 2000, basin scale groundwater exploitation has been estimated using gravity measurements from the GRACE satellites [Longuevergne et al., 2010; Rodell et al., 2009]. The GRACE satellite measurements have brought to light the severity of the depletion of many major aquifers. The depletion rate was higher in sub-humid to arid areas where water demand was greater compared to other zones, and there was a progressive increase in the depletion rate over time. Even though large-scale changes in groundwater budgets give a picture of global groundwater exploitation, it is important to have a high resolution study because depletion varies considerably as a function of location [Aeschbach-Hertig and Gleeson, 2012].

2.3.2 Application of Global hydrological models to estimate GWD

2.3.2.1 Overview of global hydrological models (GHM)

A search of the literature shows that 12 global hydrological models have been developed to date. Global scale studies started appearing in the scientific literature in the late 1980s after Vörösmarty et al. [1989] developed a global hydrological model (WBM/WTM) by integrating a Water Balance Model (which predicts evapotranspiration, soil moisture and runoff) with a Water Transport Model (which routes runoff generated using a linear reservoir model). WBM/WTM is a distributed parameter model capable of operating from regional to global scales. The initial version of WBM/WTM did not consider irrigation. Later it was modified to include irrigation, reservoir operations and permafrost [Sood and Smakhtin, 2015]. Several models viz. Macro-PDM (Macro Probability Distribution Model) [Arnell, 1999], MPI-HM (Max Planck Institute Hydrology Model) [Hagemann and Dümenil, 1997] and GWAVA (Global Water Availability Assessment model) [Meigh and Tate, 2002] were
developed with the same concept as that of WBM/WTM. All the above-mentioned models were based on single layer soil profiles, which restricted their ability to account for vertical heterogeneity in soil profiles. The concept of multiple soil layers was introduced in GHMs with the development of the Variable Infiltration Capacity model (VIC model) by the University of Washington, Seattle, USA in 2001 [Nijssen et al., 2001]. In this model, the soil profile was divided into two layers (the second layer was modelled as a nonlinear reservoir). Even though all earlier models simulated the overall water balance satisfactorily considering climate variability, none considered anthropogenic influences on the water balance.

To investigate anthropogenic impacts on water balance, Alcamo et al. [2003] developed the WaterGAP (Water – Global Analysis and Prognosis) model. WaterGAP consists of two main components: (1) a Global Water Use Model, which represents water use intensity (per unit use of water) variations driven by socio economic factors in the agricultural, industrial and domestic sectors; and (2) a Global Hydrology Model, which estimates discharge components including surface runoff and recharge by employing a water balance with daily time step [Alcamo et al., 2003]. Development of WaterGAP enabled global-scale assessment of water resources and water use per sector for the first time. However, the groundwater representation in this model is not very robust compared to PCR GLOBWB [Van Beek and Bierkens, 2009] and MATSIRO [Takata et al., 2003]. In PCR GLOBWB, discharge and storage are modelled using a kinematic wave approximation and first order linear reservoir approach, respectively. MATSIRO, which is a modification of the H08 model uses an unconfined groundwater representation with two-way interaction between the saturated and unsaturated layer of soil. MATSIRO is also capable of considering dynamic water table depth and dynamically links water withdrawal as well as surface water and groundwater interaction [Pokhrel et al., 2015]. All these models have spatial resolutions of 0.5 degrees or less, which is governed by the availability of global data sets. This coarse resolution restricts the applicability of GHMs for representations of hydrological detail at the basin scale or smaller. However, they find application in many areas of research at larger scales. In the following section the application of GHMs for estimating groundwater depletion is discussed.
2.3.2.2 Global GWD modelling

Groundwater depletion estimation has always been challenging due to large data constraints. For estimating large scale GWD, three different methods are usually adopted, (1) use of ground based measurement in a regional groundwater flow model [Konikow, 2011; Postel et al., 1996] (2) use of GHMs [Pokhrel et al., 2015; Wada et al., 2010] and (3) use of remote sensing satellite products such as GRACE [J Famiglietti et al., 2011]. The first method of depletion estimation is data intensive and demands high quality groundwater monitoring data. This limits its application in data scarce areas especially in developing countries. Therefore, application of GHMs in combination with satellite products has gained more popularity for macro scale GWD evaluations.

Global GWD estimation using GHMs is a relatively under-explored area of study compared to surface water depletion. However, a few attempts have been made to quantify the rate of GWD using GHMs (Table 2.2). Wada et al. [2010] estimated GWD using PCR-GLOBWB model (flux-based method) and found that the depletion rate had tripled over the last 50 years. However, these estimates were 30% less than regionally reported groundwater depletion. Discrepancies between model estimates and regional field estimates were eliminated to a certain extend by Doell et al. [2014] through the integration of GHM (WaterGAP) with more reliable satellite observations and field data.

Table 2.2 Groundwater depletion estimates by three different GHMs

<table>
<thead>
<tr>
<th>Model</th>
<th>GWD (km$^3$/y)</th>
<th>Year</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCR-GLOBWB</td>
<td>283 (±40)</td>
<td>2010</td>
<td>Wada et al. [2010]</td>
</tr>
<tr>
<td>PCR-GLOBWB</td>
<td>204 (±30)</td>
<td>1990 – 2000</td>
<td>Wada et al. [2012a]</td>
</tr>
<tr>
<td>MATSIRO</td>
<td>455 (±42)</td>
<td>2000</td>
<td>Pokhrel et al. [2015]</td>
</tr>
<tr>
<td>WaterGAP</td>
<td>113</td>
<td>2000 – 2009</td>
<td>Doell et al. [2014]</td>
</tr>
</tbody>
</table>
Though GHMs have proved to be useful in estimating groundwater depletion, they are data intensive and are not always publicly available. An alternative way of evaluating groundwater depletion is by using empirical models to estimate groundwater availability and comparing it with statistical data on demand. This method has been successfully applied at local to regional scales; however, no one has used it to model the depletion at the global scale. This is a research gap that is addressed in this study.

2.3.3 Groundwater stress indicators

Complex water deficit dynamics have often been represented using simple water stress indices designed to inform water resource managers and decision makers without professional backgrounds in water science. Physical stress on water resources is generally defined as ratios between demand and availability [Tom Gleeson and Wada, 2013]. The Falkenmark Indicator, the Water Resources Vulnerability Index, and the Physical and Economic Scarcity Indicators are the commonly used stress indicators to evaluate physical and economic stress [Falkenmark et al., 1989; Seckler, 1998; Shiklomanov, 1998; Sullivan et al., 2003]. The stress indicators mentioned above are simple and user friendly, but their capability of capturing seasonal and intra-national variability in supply and demand is limited. In order to overcome these limitations, the International Water Management Institute Indicator (IWMI) developed an index based on the portion of the renewable water resource available for human requirements with respect to primary water supply. The various stress indicators have proved very effective instruments to understand the overall status of a system. However, the simplification of the processes often leads to loss of information and their estimation is often limited by data availability. The advantages and disadvantages of the different water stress indicators are given in Table 2.3. It should be noted that, most of these water stress indicators focus on surface water, ignoring groundwater, even in regions where its use is predominant [Tom Gleeson and Wada, 2013].
Table 2.3 Advantages and disadvantages of water stress indicators

<table>
<thead>
<tr>
<th>Stress Indicator</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Falkenmark Water Stress Indicator</td>
<td>• National level stress indicator</td>
<td>• Does not account for water quality and accessibility</td>
</tr>
<tr>
<td></td>
<td>• Required data are easily accessible</td>
<td>• Not suitable for smaller temporal or spatial scales</td>
</tr>
<tr>
<td></td>
<td>• Easy to use and interpret</td>
<td>• Does not account for artificial water sources</td>
</tr>
<tr>
<td>Basic Human Needs Index</td>
<td>• National level stress indicator</td>
<td>• Disregards regional variations and water quality</td>
</tr>
<tr>
<td></td>
<td>• Focuses on basic human water needs</td>
<td>• Does not distinguish between industrial, agricultural and environmental water use</td>
</tr>
<tr>
<td>Social Water Stress Index</td>
<td>• Modified version of the Falkenmark Indicator</td>
<td>• Difficult to get required data</td>
</tr>
<tr>
<td></td>
<td>• Considers society’s adaptive capacity to water stress</td>
<td></td>
</tr>
<tr>
<td>Water Resource Vulnerability Index</td>
<td>• Takes into consideration water demand variations between the countries</td>
<td>• Neglects water withdrawals that are recycled and reused</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Takes no account of artificial water sources</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Takes no account of national adaptation</td>
</tr>
<tr>
<td>Indicator</td>
<td>Characteristics</td>
<td>Capacity to Water Stress</td>
</tr>
<tr>
<td>------------------------------------------------</td>
<td>---------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td><strong>International Water Management Institute (IWMI) Indicator</strong></td>
<td>Takes into account of the renewable water resource</td>
<td>Not easy to use and interpret</td>
</tr>
<tr>
<td></td>
<td>Considers infrastructure like desalination plants</td>
<td>Do not take into account individual stress adaptation capacity</td>
</tr>
<tr>
<td></td>
<td>Evaluates national stress adaptation capacity</td>
<td></td>
</tr>
<tr>
<td></td>
<td>More comprehensive and complex</td>
<td></td>
</tr>
<tr>
<td><strong>Water Poverty Index</strong></td>
<td>Consists of five key components; physical water availability, water accessibility, efficiency of water management, water use and environmental integrity of water.</td>
<td>Very complex and difficult to interpret</td>
</tr>
<tr>
<td></td>
<td>Suitable for small scale analysis</td>
<td>Extensive inputs and expert involvement are required</td>
</tr>
<tr>
<td><strong>Agricultural Water Poverty Index</strong></td>
<td>Measures water scarcity particularly for agricultural water</td>
<td>Complex and multidimensional</td>
</tr>
<tr>
<td></td>
<td>Considers both quality and quantity</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Best suited for small scale uses</td>
<td></td>
</tr>
</tbody>
</table>

To address the lack of groundwater focused indicators, the UNESCO/IAEA/IAH joint working group developed a new group of groundwater indicators to evaluate natural and
human impacts on groundwater systems across space and time [B Webb, 2006]. As a result, 10 groundwater indicators were developed to describe different aspects of groundwater systems. A detailed description of the indicators is given in Table 2.4. The groundwater indicators focus mainly on simplification, quantification, communication and comparability of complex groundwater problems [B Webb, 2006]. Over the years several other groundwater sustainability indicators have been developed to qualitatively and quantitatively study the sustainable yield of aquifers [Molina et al., 2012; Pandey et al., 2011]. However only Wada et al. [2012a] have quantitatively discretised irrigation demands met from both renewable and non-renewable groundwater, which is essential in order quantify real stresses on groundwater systems.

Table 2.4 Description of groundwater indicators developed by the UNESCO/IAEA/IAH joint working group

<table>
<thead>
<tr>
<th>Groundwater Indicator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Renewable groundwater resources per capita</td>
<td>• Expresses the total annual amount of renewable groundwater resources (m$^3$/y) per capita at national or regional level</td>
</tr>
<tr>
<td>Total groundwater abstraction/Groundwater recharge</td>
<td>• Expresses stress as fraction of total water availability</td>
</tr>
<tr>
<td>Total groundwater abstraction/Exploitable groundwater resources</td>
<td>• Expresses stress as fraction of total water availability considering prevailing economic, technological and institutional constraints and environmental conditions</td>
</tr>
<tr>
<td>Groundwater as a percentage of total use of drinking water</td>
<td>• Expresses the relation (as percentage) between groundwater and surface water used for public drinking water supplies at national level</td>
</tr>
<tr>
<td>Groundwater depletion indicator</td>
<td>• Fraction of depleted area and total area</td>
</tr>
<tr>
<td>Non-renewable groundwater indicator</td>
<td>• Fraction of total exploitable non-renewable groundwater and total non-renewable abstraction</td>
</tr>
</tbody>
</table>
In order to effectively manage the groundwater stress, the relation between the depletion and its root causes should be known. As discussed in section 2.1.2 irrigated food production is the largest consumer of groundwater resources and so is biggest cause for depletion. Despite irrigated food production being the largest consumer of groundwater, the dynamics between groundwater stress and groundwater dependent food production is poorly quantified at global and national scales. Furthermore, no previous studies have separated food production from renewable and non-renewable groundwater extraction. This understanding is very important to effectively manage the groundwater resources in the future especially under climate change.

2.4 Hydrologic response to climate change

Climate has changed in response to a variety of natural drivers since the beginning of the atmospheric formation of planet earth. It has happened in the past, is happening in the present, and will happen in the future [Dragoni and Sukhija, 2008]. More recently, during the Anthropocene, climate change has accelerated as a result of human activity. A key difference between natural climatic changes and recent anthropogenic change is the temporal scale. Natural change occurs over thousands of years whereas anthropogenic change occurs in timescales of centuries or even decades. This accelerated change will affect hydrologic
cycle in several ways in terms of availability and demand and is a hot topic [Dragoni and Sukhiya, 2008; Green et al., 2011; Richard G. Taylor et al., 2012].

2.4.1 Climate change impact on surface water

Variations in precipitation and temperature have a significant and immediate impact on the hydrological cycle, especially on the surface water resources. Changes in the climate have resulted in drastic variations in precipitation and temperature throughout the world in the 21st century and is expected to get intensified in the future [Misra, 2013]. The Fifth Assessment Report Intergovernmental Panel on Climate Change projected that the wetter regions of the world were likely to become wetter and the drier regions will get drier [IPCC, 2014]. Studies since then have reinforced these expected trends and provided better regional understanding [IPCC, 2008; 2014]. The changes in the intensity and frequency of the precipitation will change the occurrence of flood and drought by affecting the magnitude and timing of runoff [Gosain et al., 2006]. For example, studies suggest that Sub-Saharan Africa will experience a 10% drop on the rainfall by 2050 which will result in 30-50% reduction in surface drainage [De Wit and Stankiewicz, 2006; Nyong, 2005]. In addition to the changes in the precipitation, changes in temperature are also likely to alter the hydrologic dynamics. The global temperature is predicted to increase on an average by 4°C by 2080 [IPCC, 2014; Turral et al., 2011]. The primary effect of the increasing temperature will make the snow/glacier dependent water systems more vulnerable [Dracup and Vicuna, 2005]. The Indian Space Research Organisation (ISRO) had reported that ~75% of the Himalayan glaciers are retreating, with an average shrinkage of 3.75 km in the last 15 years [Misra, 2013]. This accelerated glacier retreat raises serious concerns about the glacier fed downstream water systems including the Ganges Basin. The impact of climate change on water resources will be most on the countries financially incapable of adapting to the changes and on the Middle Eastern Arab countries who primarily depend on international water and precipitation for their needs. Changes in the spatial and temporal patterns of water availability will have repercussions on agriculture and agricultural water management as it is the primary user of water.
The anticipated impact of climate change on water availability poses a challenge for agricultural (food) production over and above the challenge of feeding an increasing population, which is projected to reach 9 billion people by 2050. Climate change will significantly increase the water demand and water availability for agriculture. Several studies show that climate is the primary regulator of crop production via temperature and water regime changes \cite{Lal,2005; Oram,1989}. About 40% of the irrigation in the world is supported by large mountain systems \cite{Turral et al., 2011}. As mentioned in the previous paragraph, most of the glaciers are retreating at an alarming rate due to global warming. This drastically reduces the water availability for crop production in the snow fed watersheds. Despite its importance, studying the climate impact on agriculture and water is challenging due to the wide uncertainty in hydroclimatic projections and the scale of GCM simulations. The hydro-agri processes are not meaningful unless it is studied at a smaller scale. There has been an increasing effort to downscale the modelling to better understand these processes locally. However, the uncertainty in the understanding the latent mechanism of climate change impact on crop productivity is very high \cite{Kang et al., 2009}.

2.4.2 Climate change impact on groundwater

While the impact of anthropogenic climate change on surface water has been widely addressed, there has been limited work on its impact on groundwater resources \cite{Kundzewicz and Doell, 2009}. Climate change mainly impacts groundwater resources in two ways 1) directly by altering various components of groundwater systems including groundwater recharge and discharge and 2) indirectly by changing groundwater demand.

2.4.2.1 Direct impact on groundwater

a) Groundwater recharge

Groundwater recharge is one of the aspects of groundwater systems most sensitive to climate change as it bridges the surface and subsurface parts of the hydrological cycle \cite{Herrera-
Groundwater recharge is climatologically influenced mostly by changes in precipitation [Aguilera and Murillo, 2009; Green et al., 2007; Vaccaro, 1992]. Any change in the temporal and spatial distribution of precipitation can affect recharge particularly in arid to semi-arid regions. As discussed earlier, various studies have found a high correlation between precipitation and groundwater recharge [Döll, 2009; Kim and Jackson, 2012; Sharma, 1989]. Generally, future groundwater recharge is expected to increase in regions with increased precipitation and vice versa [Dragoni and Sukhija, 2008]. Many regional studies have shown that climate change would increase recharge. Kovalevskii [2007] showed in his study that groundwater recharge would increase under changing climate in different parts of Russia. Yusoff et al. [2002] showed both increases and decreases in groundwater recharge in Eastern England under different emission scenarios. However, it is important to recognize that groundwater recharge is a complex process impacted by various factors in addition to precipitation [De Vries and Simmers, 2002; Green et al., 2007; P McMahon et al., 2006]. In order to better understand the impact of climate change on recharge, Sherif and Singh [1999] divided groundwater systems into confined aquifers, unconfined aquifers in wet regions, unconfined aquifers in semi-arid regions and costal aquifers. That study found that unconfined aquifers in semi-arid regions are the most vulnerable to climate change as they are highly sensitive to the timing and intensity of rainfall. In Australia, Sharma [1989] demonstrated that a ±20% change in precipitation can result in ±30% to ±80% change in recharge, depending on land use. According to Döll [2009] approximately 18% of the world’s population will be affected by ≥10% decreases in recharge, whereas ~33% will experience ≥10% increases in recharge. The impact of climate change on groundwater recharge is highly variable spatially, and it is critical that studies of recharge take this fact into account.

b) Groundwater discharge

Apart from groundwater recharge, the most important aspect of groundwater systems that can be affected by climate change is groundwater discharge. Generally, groundwater discharges to hydraulically connected surface water bodies like rivers, wetlands or the ocean.
Climate change is likely to impact both groundwater recharge and flow and water levels in hydraulically connected surface water bodies. The latter will impact fluxes between surface and groundwater systems [Dragoni and Sukhija, 2008; Meyboom, 1967; Winter, 1999]. These changes can be sufficient to alter the direction of flow with many gaining streams projected to become losing streams and vice versa [Dragoni and Sukhija, 2008]. Natural discharge from groundwater systems is heavily governed by available storage. In the later twentieth century, storage decreased drastically due to changes in the demand of many systems, and this in turn reduced the amount of natural discharge from the system. Changes in climate have an important role in governing changes in demand pattern. The effects of anthropogenic activities on the groundwater system is discussed in detail in section 2.4.2.

2.4.2.2 Human and indirect impact on groundwater

In addition to direct impacts, there are many ways in which climate change can indirectly affect groundwater resources. Studies on the indirect influence of climate change on groundwater resources have examined impacts due to alteration of soil properties [Feddema and Freire, 2001], landcover [Loukas et al., 2002], salt-water intrusion due to rising sea levels [Bobba, 2002; Sherif and Singh, 1999] and changes in water demand [Alderwish and Al-Eryani, 1999; C-C Chen et al., 2001]. However, these kinds of studies are uncommon compared to direct impact studies. Of the above-mentioned impacts, the two most important are impacts due to land cover changes and impacts due to changes in water demand.

Ever since people settled permanently and began cultivation, the natural dynamics of land use land cover (LULC) have been altered. In order to meet the increasing demand for food and other needs of the growing population, the alteration of LULC has accelerated significantly since the early 19th century. The response of managed agro-ecosystems to changing precipitation is very different from that of natural ecosystems and will significantly alter the hydrology. The shift from rainfed agriculture to irrigated agriculture has had a substantial effect on groundwater resources. Earlier the irrigation mostly used surface water resources. Later, due to climate extremes and lack of surface water availability, groundwater
irrigation became more and more popular. Increased groundwater pumping affects hydraulic heads in many aquifers, allowing upward leakage of groundwater with poorer-water quality, such as in the High Plains aquifer [P B McMahon et al., 2007]. Groundwater fed irrigation has adversely affected aquifers mostly in semi-arid regions. The North China Plain [J Chen, 2010], North west India [Rodell et al., 2009] and the High Plains aquifer in US [Longuevergne et al., 2010; Scanlon et al., 2012] are those most affected by groundwater fed irrigation. Increasing temperature had also played an important role in increasing the demand to be met from groundwater. More details on regional groundwater depletion due to excessive groundwater fed irrigation are given in section 2.3.3.

An interesting contrast to the above cases is found in the Edward aquifer in Texas, USA [Loaiciga et al., 2000] and the Chalk aquifer in eastern England [Yusoff et al., 2002] where groundwater levels have decreased irrespective of pumping rate. The depletion of these aquifers has been primarily governed by climate induced lithological and topographical degradation [Brouyère et al., 2004]. According to Feddema and Freire [2001] this climate change impact on soil degradation is very common. The water holding capacity in many African regions has been reported to be decreasing, leading to higher overland flow and reduced recharge to groundwater. Another consequence of climate change is salt-water intrusion into coastal aquifers due to sea level rise. Owing to global warming, the sea level has risen by 210 mm over the past century [Church and White, 2011] and is predicted to increase by 0.5±1.5 m within the next 50 to 100 years [Buddemeneir, 1988]. Sherif and Singh [1999] reported that a 50 cm rise in the Mediterranean sea level could cause an additional 9 km of sea water intrusion in the Nile Delta aquifer in Egypt. Bobba [2002] also modelled salt water intrusion into the Godavari Delta aquifer in India due to a climate induced rise in sea level. According to Favreau et al. [2009] the indirect impacts of climate change on groundwater systems are more dominant than direct impacts. Despite indirect impacts being dominant, little is known about it at a global scale.

Considering the potential increase in groundwater dependence in the future, it is essential to study changes in groundwater availability and demand under climate change. In other words,
an integrated understanding of the direct and indirect climate change impacts on groundwater resources is essential globally.

### 2.5 Summary and knowledge gaps

This chapter reviewed the background and current state of knowledge developments in understanding the relationship between global groundwater stress and groundwater irrigated food production. It highlights the importance of stress analysis of groundwater systems at both global and regional scales when examining the sustainability of water supply required to meet various demands in the present and the future. This chapter also outlines developments in large-scale groundwater recharge estimation, the current state of global groundwater depletion and the projected response of groundwater systems to future climate change in the context of this study’s objectives.

The key motivations and knowledge gaps that led to the formulation of this study’s objectives are as follows:

**Gap 1**: Much uncertainty exists in the relationship between groundwater recharge and various governing factors including meteorological factors, lithological factors, topographic factors and vegetation factors.

This gap leads to **Research Question 1**

*How can groundwater recharge be modelled at a global scale considering all the major controlling factors?*

**Gap 2**: Despite irrigated food production being the largest consumer of groundwater, the dynamics between groundwater stress and groundwater dependent food production is poorly quantified at global and national scales. Furthermore, no previous studies have separated food production by utilizing extraction of renewable groundwater from that utilizing non-renewable groundwater.
This gap results in Research Question 2

*What is the relationship between groundwater depletion and groundwater dependent food production at a global scale?*

**Gap 3:** The future of groundwater resources and related food production under climate change is poorly studied. Moreover, the current literature lacks an integrated approach for studying the direct and indirect impacts of climate change on groundwater resources globally.

This gap was addressed by answering Research Question 3

*What is the potential impact of changing climate on groundwater depletion and groundwater dependent food production?*

The remainder of this thesis investigates each of these three research questions in turn and then synthesizes the overall findings.
Chapter 3

Predicting Groundwater Recharge for Varying Landcover and Climate Conditions: – a Global Meta-study

3.1 Abstract

Groundwater recharge is one of the important factors determining the groundwater development potential of an area. Even though recharge plays a key role in controlling groundwater system dynamics, much uncertainty remains regarding the relationships between groundwater recharge and its governing factors at a large scale. Therefore, this study aims to identify the most influential factors on groundwater recharge, and to develop an empirical model to estimate diffuse rainfall recharge at a global-scale. Recharge estimates reported in the literature from various parts of the world (715 sites) were compiled and used in model building and testing exercises. Unlike conventional recharge estimates from water balance, this study used a multi-model inference approach and information theory to explain the relation between groundwater recharge and influential factors, and to predict groundwater recharge at 0.5° resolution. The results show that meteorological factors (precipitation and potential evapotranspiration) and vegetation factors (land use and land cover) had the most predictive power for recharge. According to the model, long term global average annual recharge (1981-2014) was 134 mm/y with a prediction error ranging from -8 mm/y to 10 mm/y for 97.2% of cases. The recharge estimates presented in this study are unique and more reliable than the existing global groundwater recharge estimates because of the extensive validation carried out using both independent local estimates collated from the literature and national statistics from Food and Agriculture Organization (FAO). In a water scarce future driven by increased anthropogenic development, the results from this study will aid in making informed decision about groundwater potential at a large scale. This chapter is published in Hydrology and Earth System Sciences Vol. 22, no. 5: 2689-2703.
3.2 Introduction

Human intervention has dramatically transformed the planet’s surface by altering land use and land cover and consequently the hydrology associated with it. In the last 100 years the world population has quadrupled, from 1.7 billion (in 1900) to more than 7.3 billion (in 2014) and is expected to continue to grow significantly in the future [Gerland et al., 2014]. During the last century, rapid population growth and the associated shift to a greater proportion of irrigated food production, led to an increase in water extraction by a factor of ~6. This eventually resulted in the over exploitation of both surface and groundwater resources, including the depletion of 21 of the world’s 37 major aquifers [Richey et al., 2015]. This depletion threatened human lives in many ways, ranging from critical reductions in water availability to natural disasters such as land subsidence [Chaussard et al., 2014; Ortiz-Zamora and Ortega-Guerrero, 2010; Phien-Wej et al., 2006; Sreng et al., 2009]. Therefore, there is a need to closely examine approaches for sustainably managing this resource by controlling withdrawal from the system.

Groundwater recharge is one of the most important limiting factors for groundwater withdrawal and determines the groundwater development potential of an area [Döll and Flörke, 2005a] Groundwater recharge connects atmospheric, surface and subsurface components of the water balance and is sensitive to both climatic and anthropogenic factors [Gurdak, 2008; Herrera-Pantoja and Hiscock, 2008b; Holman et al., 2009; Jyrkama and Sykes, 2007]. Various studies have employed different methods to estimate groundwater recharge including tracer methods, water table fluctuation methods, lysimeter methods, and simple water balance techniques. Some of these studies input recharge to numerical groundwater models or dynamically link it to hydrological models to estimate variations under different climate and land cover conditions [Aguilera and Murillo, 2009; Ali et al., 2012; Herrera-Pantoja and Hiscock, 2008b; Sanford, 2002].

In the last few decades, interest in global-scale recharge analysis has increased for various scientific and political reasons [Tögl, 2010]. L’vovich [1979] made the first attempt at a
global-scale by creating a global recharge map using baseflow derived from river discharge hydrographs. The next large scale groundwater recharge estimate was done by Döll [2002] who modelled global groundwater recharge at a spatial resolution of 0.5° using the WaterGAP Global Hydrological model (WGHM) [Alcamo et al., 2003; Döll, 2002]. In this study, the runoff was divided into fast surface runoff, slow subsurface runoff and recharge using a heuristic approach. This approach considered relief, soil texture, hydrogeology and occurrence of permafrost and glaciers for the runoff partitioning. However, WGHM failed to reliably estimate recharge in semi-arid regions [Döll, 2002]. Importantly, in that study, there was no consideration of the influence of vegetation which has been reported to be the second most important determinant of recharge by many researchers [Jackson et al., 2001; Kim and Jackson, 2012; Scanlon et al., 2005]. In subsequent years, several researchers have attempted to model global groundwater recharge using different global hydrological models and global-scale land surface models [Koirala et al., 2012a; Scanlon et al., 2006a; Wada et al., 2010].

Although a fair amount of research has been carried out to model groundwater recharge at a global-scale, most studies compared results to country level groundwater information from the FAO [FAO, 2005]. FAO statistics were based on estimates compiled from national institutions. The data estimation and reporting capacities of national agencies vary significantly and raise concerns about the accuracy of the data [Kohli and Frenken, 2015]. In addition, according to FAO AQUASTAT reports, most national institutions in developing countries prioritise subnational level statistics over national level statistics, and in most cases, data is not available for all subnational entities. This decreases the accuracy of country wide averages and raises concerns about the reliability of using them as standard comparison measures. Very few studies had validated modelled estimates against small scale recharge measurements. Döll and Fiedler [2007] used 51 recharge observations from arid/semi-arid regions for adjusting the model outputs. In comparison to it, this study does a more extensive validation of the model against 715 local recharge measurements. Moreover, previous researches have been mostly restricted to studying meteorological influences on recharge, few studies have systematically explored global-scale factors governing recharge. Much
uncertainty still exists about the relationship between groundwater recharge and
topographical, lithological and vegetation factors. Without adequate knowledge of these
controlling factors, our capacity to sustainably manage groundwater globally will be
seriously compromised.

The major objectives of this study are to identify the most influential factors on groundwater
recharge and to develop an empirical model to estimate diffuse rainfall recharge.
Specifically, to quantify regional effects of meteorological, topographical, lithological and
vegetation factors on groundwater recharge using data from 715 globally distributed sites.
These relationships are used to build an empirical groundwater recharge model and then the
global groundwater recharge is modelled at a spatial resolution of 0.5° x 0.5° for the time

3.3 Methods

3.3.1 Dataset

This study is based on a compilation of recharge estimates reported in the literature from
various parts of the world. This dataset is an expansion of previously collated sets of recharge
studies along with the addition of new recharge estimates [Döll and Flörke, 2005a; Edmunds
et al., 1991; Scanlon et al., 2006a; Tögl, 2010; L Wang et al., 2010]. The literature search
was carried out using Google scholar, Scopus and Web of science with related keywords
‘groundwater recharge’, ‘deep percolation’, ‘diffuse recharge’ and ‘vertical groundwater
flux’. Several criteria were considered in including each study. To ensure that the data
reflects all seasons, recharge estimates for time periods less than one year were excluded.
The sites with significant contribution to groundwater from streams or by any artificial
means were also eliminated as the scope of this research was to model naturally occurring
recharge. In order to maximize the realistic nature of the dataset, all studies using some kind
of recharge modelling were removed from the dataset. After all exclusions, 715 data points
spread across the globe remained (Figure 3.1) and were used for further analysis. Of these
studies, 345 were estimated using the tracer method, 123 using the water balance method,
and the remaining studies used baseflow method, lysimeter, or water table fluctuation method. This diversity in recharge estimation has enabled us to evaluate systematic differences in various measurement techniques. The year of measurement or estimation of recharge estimates in the final dataset differed (provided as supplementary material [https://www.hydrol-earth-syst-sci.net/22/2689/2018/hess-22-2689-2018.html](https://www.hydrol-earth-syst-sci.net/22/2689/2018/hess-22-2689-2018.html)), and ranged from 1981 to 2014 (Figure 3.2(a)). This inconsistency in the data raised a challenge when choosing the timeframe for factors in the modelling exercise, particularly those showing inter annual variation. Moreover, the compiled dataset is not well representing all climate zones (Figure 3.2(c)), most of the studies were done either on arid, semi-arid or temperate zones. Pasture and cropland were the dominating land use in the dataset (Figure 3.2(b)).

Figure 3.1 Locations of the 715 selected recharge estimation sites and the corresponding recharge estimation method, used for model building.
Chapter 3 Predicting Groundwater Recharge

The next step was to identify potential explanatory factors that could influence recharge (referred to as predictors from here on). Potential predictors that were reported in the literature as having some influence on recharge were identified [Athavale et al., 1980; Bredenkamp, 1988; Edmunds et al., 1991; Kurylyk et al., 2014; Nulsen and Baxter, 1987; O'Connell et al., 1995; Pangle et al., 2014]. The choice of predictors was made based on the availability of global gridded datasets and their relative importance in a physical sense, as informed by the literature. According to the literature, the water availability on the surface for infiltration and the potential of the subsurface system to intake water are the two major controls on recharge. Different variables that can represent these two major factors were chosen as predictors in this study. The water availability is represented mainly using meteorological predictors like precipitation, potential evapotranspiration, aridity index, number of days with rainfall and vegetation characteristics. Whereas, the intake potential is represented using various quantifiable characteristics of the vadose zone. We employed 12 predictors comprising meteorological factors, soil/vadose zone factors, vegetation factors and topographic factors. However, other factors which could have a sizable influence on

Figure 3.2 Histograms showing frequency of (a) study year (b) Land Use and (c) Köppen Geiger Climate zones for the recharge estimates used.
recharge were not included in this study because of insufficient data. Given this, we did not consider the effects of irrigation on recharge, limiting the scope of the study to rainfall induced recharge. Subsurface lithology which can be another major factor, were also eliminated from the study, due to the lack of lithological and geological datasets at a larger scale. Better quality information about various predictors would have been desirable to enhance the accuracy of prediction. Details of predictors are given in Table 3.1.

Table 3.1 Description of predictors used for recharge model building

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Symbol</th>
<th>Unit</th>
<th>Resolution</th>
<th>Temporal span</th>
<th>Source</th>
<th>Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation</td>
<td>$P$</td>
<td>mm/y</td>
<td>$0.5^\circ$ x $0.5^\circ$</td>
<td>1981 – 2014</td>
<td>Climatic Research Unit, University of East Anglia, England</td>
<td>Mean annual precipitation</td>
<td>Harris et al. [2014]</td>
</tr>
<tr>
<td>Mean temperature</td>
<td>$T$</td>
<td>$^\circ$C</td>
<td>$0.5^\circ$ x $0.5^\circ$</td>
<td>1981 – 2014</td>
<td>Climatic Research Unit, University of East Anglia, England</td>
<td>Mean annual temperature</td>
<td>Harris et al. [2014]</td>
</tr>
<tr>
<td>Potential evapotranspiration</td>
<td>$PET$</td>
<td>mm/y</td>
<td>$0.5^\circ$ x $0.5^\circ$</td>
<td>1981 - 2014</td>
<td>Climatic Research Unit, Penman-Monteith Reference</td>
<td>Penman-Monteith Reference</td>
<td>Harris et al. [2014]</td>
</tr>
</tbody>
</table>
## Chapter 3 Predicting Groundwater Recharge

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Units</th>
<th>Source</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of rainy days</td>
<td>$R_d$</td>
<td>5 arc minutes</td>
<td>1981 – 2014</td>
<td>Average number of wet days per year defined as having $\geq 0.1$ mm of precipitation</td>
</tr>
<tr>
<td>Slope</td>
<td>$S$</td>
<td>fraction</td>
<td>-</td>
<td>Mean surface slope</td>
</tr>
<tr>
<td>Saturated hydraulic conductivity</td>
<td>$k_{sat}$</td>
<td>cm/d</td>
<td>-</td>
<td>Saturated hydraulic conductivity at 0 - 150 cm depth</td>
</tr>
<tr>
<td>Soil water storage capacity</td>
<td>$SWS_C$</td>
<td>mm</td>
<td>-</td>
<td>Texture derived soil water storage capacity in soil profile (up to 15 m depth)</td>
</tr>
</tbody>
</table>

*New et al.* [2002]  
*Verdin* [2011]  
*R W Webb et al.* [2000]
### Chapter 3 Predicting Groundwater Recharge

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Unit</th>
<th>1981–2014</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess water (without irrigation)</td>
<td>EW</td>
<td>mm</td>
<td>$\sum_{i=1}^{12} (P_i - PET_i)$ where $P_i &gt; PET_i$</td>
</tr>
<tr>
<td>Aridity index</td>
<td>AI</td>
<td>-</td>
<td>$A_1 = \frac{P}{PET}$</td>
</tr>
<tr>
<td>Clay content</td>
<td>Clay</td>
<td>%</td>
<td>Earth data, NASA 0-150cm profile</td>
</tr>
<tr>
<td>Bulk density</td>
<td>$\rho_b$</td>
<td>gm/cm$^3$</td>
<td>Earth data, NASA 0-150cm profile</td>
</tr>
<tr>
<td>Land use land cover</td>
<td>LU</td>
<td>-</td>
<td>USGS/Literature Forest, Pasture, Cropland, Urban/built up, Barren</td>
</tr>
</tbody>
</table>

Data for the chosen predictors corresponding to 715 recharge study sites were extracted from global datasets. Meteorological datasets ($P$, $T$ and $PET$) were obtained from the Climatic Research Unit, University of East Anglia, England. Even though daily data was available from 1901 to 2014 at a resolution of $0.5^0 \times 0.5^0$, in this study mean annual average of the latest 34 years (1981 to 2014) was used to reduce the inconsistency in year of recharge measurements in the final dataset. Topographic and soil data were acquired from the NASA Earth observation dataset. Both datasets were of $0.5^0 \times 0.5^0$ spatial resolution. A few of the predictors, including number of rainfall days ($R_d$) and land use/land cover ($LU$) data were obtained from AquaMaps (by FAO) and USGS (United States Geological Survey) at a spatial resolution of $0.5^0 \times 0.5^0$ and 15 arc minutes respectively. Thus, obtained $LU$ data was compared with land cover reported in literature and corrected for any discrepancies. The spatial resolution of the different data used was diverse. This was dealt with, by extracting the values for each recharge site from the original grids using the nearest neighbour...
interpolation method. As a result, predictor data extracted for each recharge site will differ from the actual value due to scaling and interpolation errors. Out of the 12 predictors $LU$ was not a quantitative predictor and was transformed into a categorical variable in the modelling exercise.

3.3.2 Recharge model development

With empirical studies, the science world is always sceptical about whether to use a single best-fit model or to infer results from several better predicting and plausible models. The former option is feasible only if there exists a model which clearly surpasses other models, which is rare in the case of complex systems like groundwater. Usually cross correlation and multiple controlling influences on the system lead to more than one model having similarly good fit to the observations. Thus, choosing explanatory variables and model structure is of significant challenge. In the past this challenge was often addressed using various step-wise model construction methods, with the final model being selected based on some model fit criteria that penalises model complexity [Fenicia et al., 2008; Gaganis and Smith, 2001; Jothityangkoon et al., 2001; Sivapalan et al., 2003]. These approaches were pragmatic responses to the large computational load involved in trying all possible models. The disadvantage of this method is that the final model will be dependent on the step-wise selection process used [Sivapalan et al., 2003]. An alternative approach for addressing this high level of uncertainty in model structure is to adopt a multi-model inference approach that compares many models [Duan et al., 2007; E Poeter and Anderson, 2005]. It typically results in multiple final models and an assessment of the importance of each explanatory variable. Therefore, this approach was used to develop an understanding of the role of different controlling factors on recharge in a data limited condition.

Choosing predictors that are capable of representing the system and selecting the right models for prediction are the key steps in the multi-model inference approach. Here, models were chosen by ranking the fitted models based on performance and comparing this to the best performing model in the set [Anderson and Burnham, 2004]. This model ranking also
provided a basis for selecting individual predictors. The analysis progressed through three key stages: exploratory analysis; model building and model testing.

3.3.2.1 Multi-model analysis

A multi-model selection process aims to explore a wide range of model structures and to assess the predictive power of different models in comparison with others. Essentially, models with all possible combinations of selected predictors are developed and assessed via traditional model performance metrics (discussed later). By conducting such an exhaustive search, multi-model analysis avoids the problems associated with selection methods in step-wise regression approaches [Burnham and Anderson, 2003]. Importantly, it reduces the chance of missing combinations of predictors with good predictive performance. However, a disadvantage of this approach is that the number of predictor combinations grows rapidly with the number of factors considered. To make the analysis computationally efficient, we set an upper limit for the number of predictors used. Another problem with this approach is that it can result in overfitting. To address this issue, we evaluated model performance with metrics that penalize complexity and tested the model robustness with a cross-validation analysis. The model development procedure using multi-model analysis is described in detail below.

(a) Exploratory Analysis

Firstly, all the chosen predictors were individually regressed against the compiled recharge dataset. This was carried out with the main objective to find the predictors having significant control on recharge and to gain an initial appreciation of how influential each predictor is compared to others. This understanding will aid in eliminating the least influential predictors from further analysis. Then assumptions involved in regression analysis, such as linearity, low multicollinearity (important for later multivariate fitting), and independent identically distributed residuals were analysed using residual analysis. Following the residual analysis, various data transformations (square root, logarithmic and reciprocal) were carried out to reduce heteroscedasticity and improve linearity of the variables. The square root transformed
recharge along with non-transformed predictors gave the most homoscedastic relations (results not shown). Therefore, these transformed values were used in further model building exercises. Predictors were selected and eliminated based on statistical indicators such as adjusted coefficient of determination ($R^2_{adj}$) value and Root mean square error (RMSE).

(b) Model building

Multiple linear regression was employed for building the models as the transformed dataset did not exhibit any nonlinearity. Furthermore, the presence of both negative and positive values in the dataset restricted the applicability of other forms of regression like log-linear and exponential [Saft et al., 2016a]. Linear regression is known for its simple and robust nature in comparison to higher order analysis. The robustness of linear regression helped to maintain parsimony together with reasonable prediction accuracy. A rigorous model building approach was adopted in order to capture the interplay between predictors with combined/interactive effects on groundwater recharge. This is an exhaustive search in which all candidate models are fitted and intercompared using performance criteria. In a way, this modelling exercise used a top-down approach, starting with a simple model which is expanded as shortcomings are identified [Fenicia et al., 2008].

(c) Model testing

The analysis above provided insight into the relative performance of the models. However, it is also important to assess the dependence of the results on the particular sample. Therefore, we conducted a subsample analysis in which the same method was re-applied to subsamples of the data. Finally, predictive uncertainty was estimated through leave-one-out cross validation. In the first case, the whole model development process was redone multiple times using subsamples of the data. To achieve this, the entire dataset was randomly divided into 80% and 20% subsets and 80% of the data were used for building the model. The predictive performance of the developed model was tested against the omitted 20% of data. This was repeated 200 times, in order to eliminate random sampling error. The leave-one-out cross validation was applied to the best few individual model structures and provided an
estimate of predictive performance for those particular models. It also gave an indication of data quality at each point.

In summary the key steps in the multi-model analysis were:

1. Selecting predictors
2. Fitting all possible models consisting different combinations of predictors
3. Calculating model performance metrics for each model
4. Calculating the “weight of evidence” for each predictor based on the performance metric of all models containing that predictor
5. Testing the predictive performance of the models.

3.3.2.2 Ranking models and predictors

Model performance was evaluated using several information criteria. These information criteria include a goodness of fit term and an overfitting penalty based on the number of predictors in the model. In this study we used $R^{2}_{adj}$, the Consistent Akaike Information Criterion (AICc), and the Complete Akaike Information Criterion (CAIC) as the performance evaluation criteria. These criteria differ in terms of penalising overfitting. $R^{2}_{adj}$ penalises over-fitting the least, AICc moderately, and CAIC heavily. However, when we are unsure of the true model and whether it over fits or not, there is some advantage in employing several criteria as it gives insight into how the results depend on the criteria used. Suitability of the information criteria also varies with the sample size. CAIC acts as an unbiased estimator for large sample size with relatively small candidate models but produces large negative bias in other cases. Whereas, AICc is well suited for small-sample applications [Cavanaugh and Shumway, 1997; Hurvich and Tsai, 1989]. The formulas for the above criteria are as follows:

$$AIC = -2 \times llf + 2 \times k \quad [Akaike, 1974]$$  \[3.1\]

$$AICc = AIC + (2 \times (k - 1) \times \frac{k+2}{n-k-2}) \quad [Hurvich and Tsai, 1989]$$  \[3.2\]

$$CAIC = -2 \times llf + k \times (\ln(n) + 1) \quad [Bozdogan, 1987]$$  \[3.3\]
\[ R^2 = 1 - \left[ \frac{n-1}{n-k-1} \right] \times [1 - R^2] \quad [\text{Ezekiel, 1929; Z Wang and Thompson, 2007}] \quad [3.4] \]

where \( -\) is the log-likelihood function, \( k \) is the dimension of the model, and \( n \) is the number of observations.

When assessing candidate models there are two aspects which are of particular interest: (1) which models are better? and (2) how much evidence exists for each predictor in predicting recharge? Analysis of the AICc and CAIC was used to answer both these questions. Models were ranked using information criteria, with smaller values indicating better performance. Information criteria are more meaningful when they are used to evaluate the relative performance of the models \[E Poeter and Anderson, 2005\]. Models were ranked from best to worst by calculating model delta values (\( \Delta \)) and model weights (\( W \)) as follows:

\[ \Delta_i = AIC_i - AIC_{\text{min}} \quad [3.5] \]
\[ W_i = \exp(-0.5 \times \Delta_i) / \sum \exp(-0.5 \times \Delta_m) \quad [3.6] \]

where, \( AIC_{\text{min}} \) is the information criteria value of the best model. \( \Delta_i \) and \( W_i \) represent the performance of \( i^{th} \) model in comparison with the best performing model in the set of \( M \) models.

Evidence ratios were then calculated as the ratio of the \( i^{th} \) model weight to the best model weight. They can be used as a measure of the evidence for the \( i^{th} \) model compared to the other models. They also provide means to estimate the importance of each predictor. This involves transformation of evidence ratios into a Proportion of evidence (PoE) for each predictor. PoE for a predictor is defined as the sum of weights of all the models containing that particular predictor. PoE ranges from 0 to 1. The closer the PoE of a predictor is to 1, the more influential that predictor is.
3.3.3 Global groundwater recharge estimation

The best model (model 1 Table 3.3) from the above analysis was used to build a global recharge map at a spatial resolution of $0.5^0 \times 0.5^0$. Recharge estimation was done annually for a study period of 34 years (1981–2014), and the estimated groundwater recharge was then averaged over the 34-year period to produce a global map. In addition to this, maps showing percentage of rainfall becoming recharge, and standard deviation of annual recharge over the 34 years were also generated. As recharge data from regions with frozen soil were scarce in the model building dataset, the model predictions in those regions particularly for regions with Köppen-Geiger classification Dfc, Dfd, ET and EF are not highly reliable. EF regions of Greenland and Antarctica were excluded from the final recharge map due to lack of both recharge and predictor data. However, the modelled recharge for Dfc, Dfd and ET regions were included because of the availability of predictor data. In addition, the modelled recharge values were compared against country level statistics from FAO [2005] for 153 countries.

3.4 Results

The results address three important questions. 1. Which are the most influential predictors of groundwater recharge? 2. What are the better models for predicting recharge? 3. How does groundwater recharge vary over space and time? The first question was answered by carrying out an exploratory data analysis and also by estimating the PoE for each predictor, the second using information criteria and the third by mapping recharge at $0.5^0 \times 0.5^0$ using the best model.

3.4.1 Exploratory data analysis

Table 3.2 gives the statistical summary of predictors and groundwater recharge at 715 data sites. It is apparent from the table that predictors varied considerably between sites, consistent with inter-site variability in regional physical characteristics. This variability provided an opportunity to explore recharge mechanisms in a range of different physical
environments. As we used linear regression to study the one to one relationship of recharge with each of the predictors, RMSE and bias of fitting were used to identify the predictors with the most explanatory power. In this case, RMSE values ranged between 23.2 mm/y for $P$ and 30.21 mm/y for $S$. Predictive potential of meteorological predictors was greater than for other classes of predictor. (Figure 3.3). $P$, $AI$, $EW$ and $\rho_b$ had a negative bias whereas, all other predictors had a positive bias.

![Figure 3.3 Model fit performance criteria for single predictor regressions.](image)

**Table 3.2 Summary statistics of potential predictors from the dataset used in this study**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$ (mm/y)</td>
<td>1.30</td>
<td>2627.00</td>
<td>2625.70</td>
<td>572.82</td>
<td>305.65</td>
</tr>
<tr>
<td>$T$ ($^\circ$C)</td>
<td>1.60</td>
<td>30.62</td>
<td>29.02</td>
<td>17.73</td>
<td>6.04</td>
</tr>
<tr>
<td>$PET$ (mm/y)</td>
<td>6.60</td>
<td>2600.00</td>
<td>2593.40</td>
<td>1356.17</td>
<td>401.77</td>
</tr>
<tr>
<td>$Rd$ (d/y)</td>
<td>2.00</td>
<td>270.00</td>
<td>268.00</td>
<td>85.89</td>
<td>42.78</td>
</tr>
<tr>
<td>$S$</td>
<td>0.00</td>
<td>10.16</td>
<td>10.15</td>
<td>0.84</td>
<td>1.17</td>
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<td>$k_{sat}$ (cm/d)</td>
<td>0.00</td>
<td>265.75</td>
<td>265.75</td>
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<td>$SWSC$ (mm)</td>
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<td>1121.00</td>
<td>1119.00</td>
<td>517.38</td>
<td>240.81</td>
</tr>
<tr>
<td>$AI$</td>
<td>0.00</td>
<td>68.18</td>
<td>68.18</td>
<td>0.70</td>
<td>3.74</td>
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</tbody>
</table>
3.4.2 Multi-model analysis

3.4.2.1 Proportion of evidence (PoE) for individual predictors

Figure 3.4 shows the PoE of the 12 predictors used in this study. According to this analysis, 3 of the 12 predictors stood out as having the greatest explanatory power (Figure 3.4). Precipitation ($P$), Potential evapotranspiration ($PET$) and Land use land cover ($LU$) had the highest proportions of evidence (~1). Subsurface percentage of clay ($Clay$) and Saturated hydraulic conductivity ($k_{sat}$) also had an important influence on recharge with PoE ~0.4. Aridity index ($AI$), Rainfall days ($Rd$), Mean temperature ($T$), Bulk density ($\rho_b$), Slope ($S$), Excess water ($EW$) and Soil water storage capacity at root zone ($SWSC$) were in the lower PoE range (<0.1 according to both the criteria). There was some variation in the PoE value of the predictors with performance metric, due to the diversity in over-fitting penalty. However, ranking of the variables was identical irrespective of the performance metric used. The ‘best’ and ‘worst’ predictors ranked according to $R^2_{adj}$ were also in agreement with the PoE analysis (not shown). In addition, results of the subsample analysis gave similar results (not shown).

3.4.2.2 Better performing models

According to information criteria, the performance of models can only be evaluated relative to the best performing model in the set. In this study, as per the model weights, no model exhibited apparent dominance. The evidence ratio (ratio between the weights of the best model and $n^{th}$ model) suggested that the best model according to CAIC was only 1.04 times better than the 2nd best model, moreover, the adjusted $R^2$ values of the top 10 models vary
only slightly (0.33 to 0.35) (Table 3.3). However, the evidence ratio increased exponentially with increase in model rank and there was a clear distinction between better models and worse models. Similar results were reported by Saft et al. [2016b] in her work for modelling rainfall-runoff relationship shift. The choice of better models was made by considering the PoE of individual predictors (refer section 3.4.2.1) and the number of predictors in the model (V). Figure 3.5 shows the performance criteria for the top three models for different V values. The model performance increased with V up to 6 to 7 depending on the different criteria. After that, AICc, CAIC, RMSE and R²_adj values remained almost constant, indicating that further addition of predictors did not improve the model performance. In particular CAIC shows reaches a minimum at V=7 and it penalises model complexity more rigorously. Table 3.3 illustrates the predictors in the top 10 models selected based on CAIC. All the top 10 models had V ≤ 7. P, PET and LU repeatedly appeared in the predictor list of the top ten models substantiating their high predictive capacity, and the top ranked model includes these three predictors only. In this particular case, top performing models according to both information criteria were the same, therefore results from only one criteria (CAIC) will be discussed.

Figure 3.4 Proportion of evidence according to AICc and CAIC for 12 predictors (sorted in descending order of PoE).
Figure 3.5 (a) $R^2_{adj}$ (b) CAIC and (c) RMSE for the top 3 models with different number of predictors up to 12 and the green dotted lines representing the number of predictors for the best performance criteria value.

Table 3.3. Coefficient of predictors used in the top 10 models, ranked based on CAIC

<table>
<thead>
<tr>
<th>P</th>
<th>T</th>
<th>PET</th>
<th>Rd</th>
<th>S</th>
<th>ksat</th>
<th>SW</th>
<th>SC</th>
<th>A</th>
<th>EW</th>
<th>ρb</th>
<th>Clay</th>
<th>LU</th>
<th>Constant</th>
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<td>0.008</td>
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<td></td>
<td></td>
<td>0.957</td>
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<tr>
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<td>-0.004</td>
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<td>0.957</td>
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<td></td>
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<td>0.957</td>
</tr>
</tbody>
</table>
3.4.2.3 Model testing

Models ranking from 1 to 10 according to CAIC (Table 3.3) were tested using both the model testing techniques discussed in section 3.3.2.1(c). Figure 3.6 depicts model fit and model prediction RMSE values of 200 subsample tests. It is clear from the boxplots that the difference between the RMSE of the 1st and the 10th model during both model fitting and prediction is less than 1 mm/y. In subsample tests, $R^2_{adj}$ of the best model ranged from 0.42 to 0.56 implying 42 to 56% of the variance was explained (please refer section 3.3.2.1 for details on subsample testing). The model errors at each data point ranged from -8 to 28 mm/y. However, 97.2% of the points had errors between -8 and 10 mm/y. Figure 3.7 shows the relation between precipitation and model errors and it is evident from this scatter plot that model predictions were not greatly influenced by low or high precipitation. In other words, the model was unbiased by precipitation trends. Similar checking was done for all other predictors (not shown) which all showed a similar pattern to precipitation. The dataset was classified based on recharge estimation techniques and model performance was tested with results showing no systematic difference (not shown).

Figure 3.6 RMSE of sub-sample (a) model fitting and (b) model prediction of top 10 models according to CAIC.
3.4.3 Global groundwater recharge

The global long term (1981 – 2014) mean annual groundwater recharge map at a spatial resolution of $0.5^\circ$ was made by the model developed in section 3.3.2 (Figure 3.8). In this study, the best model as defined by CAIC (model 1 in Table 3.3) was used to generate the recharge map. However, due to the similarity in structure of the top 10 models (Table 3.3), all models were equally good at predicting groundwater recharge and gave similar results (not shown). Grid scale recharge ranged from 0.02 mm/y to 996.55 mm/y with an average of 133.76 mm/y. The highest recharge was associated with very high rainfall (>4000 mm/y). Humid regions such as Indonesia, Philippines, Malaysia, Papua New Guinea, Amazon,
Western Africa, Chile, Japan and Norway had very high recharge (>450 mm/y). Whereas, arid regions of Australia, the Middle East and Sahara had very low recharge (<0.1 mm/y). In humid areas, percentage of rainfall becoming groundwater recharge (>40%) was found to be very high in comparison to other parts of the world. However, the mean percentage of rainfall becoming recharge is only 22.06% across the globe. Among all the continents, Australia had the lowest annual groundwater recharge rate.

Figure 3.8 Long-term (1981 -2014) average annual groundwater recharge estimated using the developed model.

Figure 3.9 Temporal distribution of total global recharge along with total global precipitation of corresponding years for a period of 1981 to 2014.
Over the 34 years, global annual mean recharge followed the same pattern as that of global annual mean precipitation (Figure 3.9). Least recharge was predicted in the year 1987 (groundwater recharge=95 mm/y), where the annual average rainfall was <180 mm/y. Variation in recharge over the years was maximal in arid regions of Australia and North Africa (Figure 3.10(a)). However, the standard deviation of recharge was higher in humid areas than in arid regions (Figure 3.10(b)). This indicates that standard deviation did not clearly represent year to year variations in recharge. Potentially, the advantage of using coefficient of variation over standard deviation is that it can capture variations even when mean values are very small. In this case precipitation and potential evapotranspiration were the two major predictors of recharge. Globally, variability in evapotranspiration is much less than variability in rainfall [Peel et al., 2001; Trenberth and Guillemot, 1995]. Therefore, variability of groundwater recharge both temporally and spatially is due to variability in precipitation, which implies that arid regions are more susceptible to inter-annual variation in groundwater recharge. A comparison of predicted recharge against country level recharge estimates from FAO [2005] shows that the model tends to over predict recharge, particularly for low recharge areas. However, due to inaccuracies in the FAO estimates this cannot be considered as a reliable comparison (Figure 3.11(a)). Recharge estimates from the best models in the present study were compared to recharge estimates from the complex hydrological model (WaterGAP) (Figure 3.11(b)). Even though the model in this study overestimates recharge for countries with fewer data points, the scatter shows a smaller spread compared to the FAO estimates. Figure 3.12 shows the country wide distribution of errors in model prediction in comparison with FAO statistics. Very high errors were found in countries with fewer model building data points. The extra spread in the scatter in Figure 2.11 may have a variety of reasons, for example discrepancies in the country scaling and errors in the FAO/WaterGAP. The model considerably overestimated recharge for Russia, Canada, Brazil, Indonesian Malaysia and Madagascar where the recharge sample points were relatively few.
3.5 Discussion

The aims of this study were to identify the factors having the most influence on groundwater recharge, and to develop a global model for predicting groundwater recharge under limited data conditions, without extensive water balancing. In this study, an empirical model building exercise employing linear regression analysis, multi-model inference techniques and information criteria was used to identify the most influential predictors of groundwater recharge and use them to build predictive models. Finally, a global groundwater recharge map was created using the developed model. The key findings from this study and their implications for future research and practice with respect to global groundwater recharge are discussed below.
One of the findings to emerge is that, out of numerous models developed in this study there was no single best model for groundwater recharge. Instead, there were clear sets of better and worse models. However, there were predictors which stood out as having greater explanatory power. Of the 12 predictors chosen for the analysis, meteorological \((P, PET)\) and vegetation predictors \((LU)\) had the most explanatory information followed by saturated hydraulic conductivity and clay content. Thus, models using these predictors ranked higher according to information criteria. It is reasonable that meteorological factors had the most explanatory information. In most cases, especially dry regions, groundwater recharge is controlled by the availability of water at the surface, which is mainly controlled by precipitation, evapotranspiration and geomorphic features [Scanlon et al., 2002]. Numerous studies agree with this finding. For example, in south western USA, 80% of recharge variation is explained by mean annual precipitation [Keese et al., 2005b]. However, the influence of meteorological factors on groundwater recharge is highly site-specific [Döll and Flörke, 2005a]. The effect of meteorological factors can also depend on whether the season...
or year is wet or dry, type of aquifer and irrigation intensity [Adegoke et al., 2003; Moore and Rojstaczer, 2002b; Niu et al., 2007].

Many studies have reported vegetation related parameters as the second influential predictor of groundwater recharge. Vegetation has a high correlation with other physical variables such as soil moisture, runoff capacity and porosity, which adds to its recharge explanatory power [Kim and Jackson, 2012; Scanlon et al., 2005]. In this study Land Use (LU) was used as a proxy for vegetation. According to the results, LU was found to be one of the predictors having the highest Proportion of Evidence (PoE) (Figure 3.4). In addition, all the better performing models included LU as one of the predictors which clearly indicates that vegetation is one of the most influential factors for groundwater recharge. Results indicates that recharge rate was high, where runoff water have more retention time on the surface. This was mainly observed for shallow rooted vegetation like grasslands. In deep rooted forest areas recharge was reduced because of increased evapotranspiration [Kim and Jackson, 2012]. However, not all reported studies are in agreement with vegetation as an important predictor of recharge. For example, Tögl [2010] failed to find a correlation between vegetation/land cover and recharge. This may be the result of some peculiarity in the study dataset. Apart from the predictors discussed above, depth to groundwater and surface drainage density were also identified as potential predictors of recharge from literature [Döll and Flörke, 2005a; Jankiewicz et al., 2005]. Despite this they were excluded from this study because of the lack of appropriate resolution global datasets.

The total recharge estimated in this study is strongly consistent with results from complex global hydrological models. Long term average annual recharge was found to be 134 mm/y. The total recharge estimated in this study (13,600 km³/y) was very close to existing estimates of complex hydrological models except those using MATSIRO, which overestimates recharge in humid regions [Koirala et al., 2012b]. The results shown in Table 3.4 indicate that, compared to existing techniques, the model developed in this study can make recharge assessments with the same reliability but with fewer computational requirements. Moreover,
the error in recharge prediction in this study was low, ranging from only -8 mm/y to 10 mm/y for 97.2% of cases.

Table 3.4 Global estimates of groundwater recharge

<table>
<thead>
<tr>
<th>Model Used</th>
<th>Spatial Resolution</th>
<th>Temporal Range</th>
<th>Total Global Recharge (km³/y)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Empirical model</td>
<td>0.5deg</td>
<td>1981-2014</td>
<td>13,600</td>
<td>Current study</td>
</tr>
<tr>
<td>WaterGAP 2</td>
<td>0.5deg</td>
<td>1961-1990</td>
<td>14,000</td>
<td>Döll, [2002]</td>
</tr>
<tr>
<td>WaterGAP</td>
<td>0.5deg</td>
<td>1961-1990</td>
<td>12,666</td>
<td>Döll and Flörke, [2005]</td>
</tr>
<tr>
<td>PCR GlobWB</td>
<td>0.5deg</td>
<td>1958-2001</td>
<td>15,200</td>
<td>Wada et al., [2010]</td>
</tr>
<tr>
<td>PCR GlobWB</td>
<td>0.5deg</td>
<td>1960-2010</td>
<td>17,000</td>
<td>Wada et al., [2012]</td>
</tr>
<tr>
<td>MATSIRO</td>
<td>1deg</td>
<td>1985-1999</td>
<td>29,900</td>
<td>Koirala et al., [2012]</td>
</tr>
</tbody>
</table>

The global recharge map developed showed a similar pattern to recharge maps produced using complex global hydrological models. The results of this study indicate that recharge across the globe was varied considerably as a function of spatial region, and was analogous to global distribution of climate zones [Scanlon et al., 2002]. Humid regions had very high recharge compared to arid (semi-arid) regions, which is obviously due to the higher availability of water for recharge. Recharge was also affected by climate variability and climate extremes at a regional level [Scanlon et al., 2006a; Wada et al., 2012b]. However, an effect of climate variability on inter annual recharge at a global-scale was not pronounced in our results. The potential reason for this is that the El Nino Southern Oscillation (ENSO), the primary factor that determines climate variability globally, has converse effects in different parts of the world. The effects of increased precipitation in some parts of the world would have been counteracted by reductions in precipitation in other areas resulting in relatively small effect on inter annual variation in global recharge.
3.6 Conclusion

This study presents a new method for identifying the major factors influencing groundwater recharge and using them to model large scale groundwater recharge. The model was developed using a dataset compiled from the literature and containing groundwater recharge data from 715 sites. In contrast to conventional water balance recharge estimation, a multi-model analysis technique was used to build the model. The model developed in this study is purely empirical and has fewer computational requirements than existing large-scale recharge modelling methods. The 0.5° global recharge estimates presented here are unique and more reliable because of the extensive validation done at different scales. Moreover, inclusion of a range of meteorological, topographical, lithological and vegetation factors adds to the predictive power of the model. The results of this investigation show that meteorological and vegetation factors had the most predictive power for recharge. The high dependency of recharge on meteorological predictors make it more vulnerable to climate change. Apart from being a computationally efficient modelling method, the approach used in this study has some limitations. Firstly, it does not include direct anthropogenic effects on the groundwater system and also excludes focused recharge by natural or artificial means, suggesting scope for further future development. Secondly, the recharge data set used in this study did not include data points from frozen regions. Therefore, Greenland and Antarctica were excluded from the final recharge map. However, the model developed in this study and the recharge maps produced will aid policy makers in predicting future scenarios with respect to global groundwater availability.
Chapter 4

Global Assessment of Groundwater Stress from Irrigated Food Production

4.1 Abstract

Groundwater is an essential resource for agricultural development across the globe. Due to poor water resource management, groundwater dependent agriculture induces substantial stress on many groundwater systems; however, the assessment of such stress is often neglected. This study aimed to estimate stress on groundwater systems resulting from agricultural irrigation particularly irrigated food production. This study also explored various pathways for stress reduction via improved irrigation efficiency and increased productivity. The stress on groundwater systems was analysed using the ratio of water use to water availability, allowing for environmental requirements. Most of the data for this analysis were from modelling or international agencies like the FAO (Food and Agriculture Organization). The results showed that of 63 countries utilizing groundwater for irrigation, one third are overexploiting groundwater resources, while the groundwater in one-fifth of these countries is moderate to heavily stressed. Over 80% of non-renewable groundwater abstraction is from just six countries. Further, about 450 million tonnes of global annual food production are from non-renewable groundwater exploitation. This is equivalent to the annual food consumption of a tenth of the total world population. The results from this study showed that if current irrigation efficiency were increased to 90%, groundwater stress in the most severely affected areas could be reduced by 40%. Water thus saved could also be used to produce an additional 150 million tonnes of food while maintaining groundwater stress at acceptable levels. Moreover, improved water productivity in conjunction with increased irrigation efficiency could reduce the current level of unsustainable food production by 74%. The results from this study give key insights into the dynamics of irrigation stress on groundwater systems, and the role of managerial interventions. This information will help
increase sustainable food production by identifying hotspots of groundwater depletion and managing them scientifically. This chapter is under review in Global Environmental Change journal.

4.2 Introduction

Irrigated agriculture contributes 40% of the total food production from 17% of agricultural land and is the backbone of food security [Abdullah, 2006; Wada et al., 2012a]. Irrigation has played a pivotal role in agricultural booms in many countries like India and China. According to the FAO, irrigation has improved the economic output of developing countries by more than 400% [Khan et al., 2006]. Groundwater, once a temporary source for irrigation during dry seasons, has now become the primary source in many regions, especially in water-limited areas. Year-round availability and minimal infrastructure requirements make groundwater irrigation an attractive choice for farmers. Global annual groundwater extraction is 982 km³. Although withdrawn for varying purposes, 70% is used for irrigation [NGWA, 2016]. Despite all its benefits, excessive irrigation has led to serious environmental and resource issues such as water scarcity, waterlogging and salinity.

Water abstracted from groundwater storage needs to be recharged either naturally or artificially in order to maintain storage equilibrium. However, in water-limited areas, abstraction rates often far exceed recharge rates. This results in declining groundwater storage and may lead to the drying of aquifers or the use of fossil groundwater which cannot be replenished [T Gleeson et al., 2010; Konikow and Kendy, 2005]. Numerous studies have attempted to quantify groundwater depletion at a regional scale using GRACE data [J Famiglietti et al., 2011; Feng et al., 2013; Joodaki et al., 2014; Rodell et al., 2009]. Despite evidence of groundwater depletion and the identification of irrigation as a dominant cause, few studies have explicitly examined the relationship between these two factors at a global scale. As food supply and demand is not locally confined, in the absence of knowledge about sustainable food production on a global scale, the ability to manage groundwater stress will be highly compromised. Moreover, often the importance of balancing human needs with
environmental requirements is ignored. This is of great concern considering the exponentially increasing world population. The rate of world’s population growth will be at its maximum in the coming 20 to 30 years, leaving us very little time to prepare for the change [Wallace, 2000]. Furthermore, global agriculture is expected to increase by ~20% in the next 50 years [Jayasekera et al., 2011; Tilman et al., 2001]. This will impose greater pressure on both surface and groundwater resources. In addition to this, regions where food production requirements are likely to increase over the coming 20 to 30 years are also those with heavily stressed groundwater systems [Foley et al., 2011]. In the current scenario of rapidly growing population, it is not a feasible option to decrease food production in order to protect groundwater systems.

Complex water deficit dynamics have often been represented using simple water stress indices designed to inform water resource managers and decision makers without a professional background in water science. Physical stress on water resources is generally defined as the ratio between demand and availability [Tom Gleeson and Wada, 2013]. Some stress indicators viz., the Falkenmark Indicator, the Water Resources Vulnerability Index, the Physical and Economic Scarcity Indicators and the Water Poverty Index have been used to evaluate physical and economic stress [Falkenmark et al., 1989; Seckler, 1998; Shiklomanov, 1998; Sullivan et al., 2003]. The Falkenmark Indicator is the simplest and most commonly used for assessment of water stress at the national level. However, it is not able to capture variability in seasonal and intra-national water demand. In order to overcome these limitations, the International Water Management Institute Indicator (IWMI) considered an index based on the portion of the renewable water resource available for human requirements with respect to primary water supply. The IWMI indicator accounts for both the physical and economic water stress of a country or a region. However, most of these water stress indices focused on surface water, ignoring groundwater, even in regions where its use is predominant [Tom Gleeson and Wada, 2013]. The UNESCO/IAEA/IAH working group developed a new group of groundwater indicators to evaluate natural and human impacts on groundwater systems across space and time [B Webb, 2006]. Over the years several other groundwater sustainability indicators have been developed to
qualitatively and quantitatively study the sustainable yield of aquifers [Molina et al., 2012; Pandey et al., 2011]. Only Wada et al. [2012a] have quantitatively discretised irrigation demands met from both renewable and non-renewable groundwater. Prolonged extraction of non-renewable groundwater results in its depletion, therefore, separate measurement of demand met from renewable and non-renewable groundwater resources is essential in order to accurately quantify real stresses on groundwater systems. Furthermore, given that low river flows are mainly supplied by the base flow contribution from groundwater, environmental baseflow should also be considered in groundwater stress assessment. Neglecting this component might lead to overestimation of water availability for extraction [Pastor et al., 2014]. However, to our knowledge, no global groundwater assessment studies have discretised irrigation demand met from renewable and non-renewable groundwater or considered environmental flow requirements. Therefore, a more scientific assessment of stress on the groundwater system is needed to improve management of this resource.

This study aims to estimate the stress of irrigated food production on groundwater systems at a global scale. In particular, it will: 1) estimate groundwater stress globally at a resolution of 0.5° and summarize that by country; 2) estimate the amount of food produced from unsustainable groundwater extraction, and 3) examine potential scenarios for reducing groundwater stress and increasing sustainable food production. In doing so, we have also incorporated an estimate of environmental base flow requirement (EBFR) into the estimate of groundwater stress.

4.3 Methods

4.3.1 Groundwater stress calculation

The stress on groundwater systems due to irrigation was assessed by estimating two factors (1) non-renewable groundwater abstraction for irrigation (NRGA) and (2) groundwater stress index (SR). NRGA was defined as the quantity of groundwater extracted for irrigation purposes that exceeded natural groundwater replenishment rates, allowing for an estimate of environmental requirements. This definition is a modified form of ‘non-renewable
groundwater abstraction’ from Wada et al. [2012a], which focused only on gross irrigation demand. In this study, we reduce recharge by an estimate of the EBFR from the groundwater system when estimating renewable water (see Section 4.3.2 for more details).

\[
NRGA = IWR - (R - EBFR) \quad [4.1]
\]

\[
SR = \frac{IWR}{\eta(R - EBFR)} \quad [4.2]
\]

Where;

NRGA = Non-renewable groundwater abstraction

\(IWR\) = Irrigation water requirement met from groundwater

\(R\) = Groundwater recharge

\(EBFR\) = Environmental baseflow requirement

SR = Stress index

\(\eta\) = Country level irrigation efficiency

Stress in the system due to irrigation was assessed by calculating the groundwater stress index (SR). SR is defined as the ratio between use and availability (Eq. 4.2) and is quite similar to the UN Commission on Sustainable Development scarcity index [Raskin et al., 1997] (See Section 4.3.2 and 4.3.3 for more details on water use and availability calculations). The SR values used in this study were classified using the Water Stress Index (WSI) scale proposed by Smakhtin (2004) for surface water resources (Table 4.1). According to WSI scale, \(SR<1\) means the rate of groundwater extraction is less than that of net natural water availability, while a \(SR>1\) means that extraction exceeds availability. In the present study annual stress indices were calculated and then averaged over three decades.

Because the WSI scale takes account of \(EBFR\), the SR values indicative of various levels of exploitation differ from those of other stress scales. For example, \(SR>0.6\) indicates heavy exploitation [Smakhtin, 2004]. Where, \(SR=0.6\) means that 40% of water remains the system even after the \(EBFR\) is met. This buffer helps prevent the use of water required for
environmental needs to meet other water demands during dry periods [Smakhtin, 2004]. Although the WSI scale is not used for categorizing groundwater stress and uses total water withdrawal for calculation of $S_R$s, it is applicable in the present study as we focused only on groundwater irrigated areas which means total water withdrawal is equivalent to total groundwater withdrawal. The groundwater stress analysis was carried out by averaging annual stress indices for a period of 34 years (1981 to 2014). In addition to this, the irrigated land use data was only available for the year 2005, therefore the results represent a climatological average for 2005 land use conditions.

Table 4.1 Groundwater stress scale based on Water Stress Indicator [Smakhtin, 2004]

<table>
<thead>
<tr>
<th>SR Range</th>
<th>Stress Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 0.1</td>
<td>Not exploited</td>
</tr>
<tr>
<td>0.1 – 0.3</td>
<td>Slightly exploited</td>
</tr>
<tr>
<td>0.3 – 0.6</td>
<td>Moderately exploited</td>
</tr>
<tr>
<td>0.6 – 1</td>
<td>Heavily exploited</td>
</tr>
<tr>
<td>&gt;1</td>
<td>Overexploited</td>
</tr>
</tbody>
</table>

4.3.2 Estimation of groundwater available for irrigation

In this study, the water availability was calculated as the recharge per grid less the $EBFR$ in that particular grid. The groundwater recharge estimates used were obtained from a global groundwater recharge model developed by the authors [Mohan et al., 2018]. This is an empirical model for estimating diffuse rainfall recharge. The model estimates groundwater recharge at an annual time step and a spatial resolution of $0.5^0$ (~55 km at equator). The model simulation was carried out for a period of 34 years (1981 to 2014) and a long-term average was used for further analysis. Recharge estimated from the model does not account for recharge by artificial means, riverine recharge or irrigation return flows. The model also considered each grid as a bucket without any inter pixel transfer of water. The cells with groundwater irrigation were directly extracted from model outputs.
EBFR was estimated using the base flow index method. The global base flow index map was obtained from the European Commission’s Global Streamflow Characteristics Dataset [Beck et al., 2015; Beck et al., 2013; Molina et al., 2012] and the percentage of mean annual runoff required for environmental flow was obtained from the Global Environmental Flow Information System of the International Water Management Institute [Smakhtin et al., 2004; Sood et al., 2017]. EBFR was calculated assuming that the percentage contribution from groundwater systems to environmental flow is equal to the baseflow index of the region. It was also assumed that groundwater was the only source of base flow in each grid. This provides an upper-bound estimate of sustainably allocable water which assumes all groundwater output flows into rivers rather than evaporating.

4.3.3 Estimation of water use

Water use was estimated as the total water withdrawn for irrigation, which was estimated by dividing IWR with country specific irrigation efficiency. IWR was modelled using the FAO GlobWAT model [Hoogeveen et al., 2015]. This high-resolution model runs at a spatial resolution of 5 arcmin and the model is in the public domain. The main advantage of using GlobWAT over other existing large-scale crop models is that it simulates incremental crop evapotranspiration resulting from irrigation. This model calculates global water balance in two steps; (1) one-dimensional vertical water balance is used to calculate rainfed evaporation and evaporation from irrigated areas and (2) horizontal water balance is used to calculate discharge from the basin considering the net irrigation demand. The crop evapotranspiration ($ET_c$) is calculated by multiplying Reference crop evapotranspiration ($ET_0$) (calculated by FAO Penman Monteith equation) with a growth stage specific crop coefficient ($K_c$) (Eq. 4.3). The $K_c$ values were derived from Global Agricultural Systems Map [FAO, 2011]. Four different $K_c$ values were used per crop corresponding to four growth stages viz., initial/sowing phase, development phase, mid phase and last/harvest phase. The grid based $ET_c$ was area weighted based on the proportion of irrigated area per grid. Then the amount of evapotranspiration ($ET_{rain}$) was then subtracted from total $ET_c$ to obtain incremental evapotranspiration due to irrigation ($ET_{inc-irri}$) (Eq. 4.4), which corresponds to the total IWR
per grid. The calculation of IWR was made in monthly time steps, then aggregated to provide annual IWR values for further analysis. Discharge components of the GlobWAT and WaterGAP models have previously been validated against discharge data from the Global River Discharge Database [Döll and Fiedler, 2007; Hoogeveen et al., 2015].

\[ ET_c(t) = k_c \times ET_0(t) \]  \[ ET_{inc-irr}(t) = ET_c(t) - ET_{rain}(t) \]

4.3.4 Non-sustainable food production from groundwater

The amount of food produced using non-renewable groundwater per country was calculated using production datasets from FAOSTAT (http://www.fao.org/faostat/en/#data). Total production using groundwater by country was calculated using average yield per hectare (which is an average of irrigated and rainfed yield) and total groundwater irrigated area (Eq. 4.5). This estimate was divided by the national groundwater withdrawal for irrigation to estimate yield per unit of groundwater withdrawn (\(Y_{pgw}\)) (Eq. 4.6).

\[ Y_{gw} = Y_{tot} \times AI_{gw} \]  \[ Y_{pgw} = \frac{Y_{gw}}{IWW_{gw}} \]

where;
\(Y_{gw}\) = Total food production from groundwater irrigated area (tonnes)
\(Y_{tot}\) = Average yield from irrigated area (tonnes/ha)
\(AI_{gw}\) = Total groundwater irrigated area (ha)
\(Y_{pgw}\) = Yield from groundwater withdrawn (tonnes/ML)
\(IWW_{gw}\) = Groundwater withdrawn for irrigation (ML)

The association between \(NRGA\) and food production (t) by country was estimated using \(Y_{pgw}\) (Figure 4.1). The yield per unit of groundwater withdrawal varied from 0.2 t/ML (Mauritania in Africa) to 26.7 t/ML (France in Europe). Europe had the highest yield per
ML of groundwater (~20 t/ML) followed by Oceania (~15 t/ML), then Asia and America (~5 t/ML) and lastly Africa (~1.5 t/ML).

Unsustainable food production from groundwater irrigation was estimated using an upper limit for SR of 0.6 for sustainable extraction (base case scenario) and estimating yield associated with the volume of groundwater extraction above this limit. After the impact of food production on groundwater stress was quantified, various possibilities for reducing stress were evaluated. Two potential pathways for controlling groundwater stress and ensuring food security are (1) improving irrigation efficiency (efficiency scenarios) by delivering a higher proportion of extracted water to the plant and (2) increasing the productivity or yield per unit of applied water in addition to improving irrigation efficiency (High efficiency and yield scenario; S3). In the former case, the irrigation efficiency of every nation was assumed to be increased to 90% (high efficiency scenario; S2). This is an ambitious limit. Therefore, a second efficiency scenario was also tested, where the efficiency of every country was assumed to be improved by 75% of the delta between current and 90% efficiency (moderate efficiency scenario; S2a). The percentage change in $SR$ for each efficiency scenario was calculated using Equation 7. In the high efficiency and yield scenario, efficiency was raised to 90% all over the globe and irrigation productivity was raised to 8 t/ML where the current productivity is less than 8 t/ML, which is double current
global mean irrigation productivity. The yield scenario gives a holistic perspective of stress remediation without compromising food security.

\[
\Delta SR = (1 - \frac{\eta}{\eta_{new}}) \times 100
\]  

[4.7]

Where;

\[\eta\] = current irrigation efficiency

\[\eta_{new}\] = efficiency in different scenarios

The three scenarios are summarized in Table 4.2.

Table 4.2 Efficiency and yield improvement scenario descriptions

<table>
<thead>
<tr>
<th>Scenario name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Base case scenario: SR ≤0.6 (representing 2005)</td>
</tr>
<tr>
<td>S2</td>
<td>High efficiency scenario: Irrigation efficiency =90%</td>
</tr>
<tr>
<td>S2a</td>
<td>Moderate efficiency scenario: Irrigation efficiency = 75% of the difference between current and maximum efficiency (90%)</td>
</tr>
<tr>
<td>S3</td>
<td>High efficiency and yield scenario: Irrigation efficiency=90%; Irrigation productivity ≥ 8 t/ML</td>
</tr>
</tbody>
</table>

4.3.5 Data sources

The data required for calculating groundwater irrigation \(SR\) and unsustainable food production were obtained from the public domain (Table 4.3). Groundwater irrigated areas were extracted using the Global Map of Irrigated Areas version 5 [Siebert et al., 2013]. This gridded irrigated land-use map, which has a resolution of 5 arc minutes, was obtained from the Food and Agricultural Organization-AQUASTAT. The reference years of this dataset ranged from 2002 to 2008 and the data were compiled from various national and subnational agencies [FAO, 2016]. On average the data corresponds to the year 2005. The area
considered in this study comprises both fully groundwater irrigated areas and combined ground and surface water irritated areas. Due to the lack of a source-based split in combined use areas, these areas were assumed to be 50% groundwater irrigated and 50% surface water irrigated.

Food production estimates used Country-wise irrigated food production statistics obtained from FAOSTAT for 150 countries [FAOSTAT, 2016]. Total irrigated food production was calculated as the sum of total cereal, pulses, root, fruits, tree nuts and vegetable production per country. Total food production per country was then averaged from 1981 to 2014. Apart from the datasets mentioned above, data requirement for calculating $R$ (viz., precipitation, potential evapotranspiration and land use) and $IWR$ (viz., precipitation, coefficient of variability of precipitation, number of rainfall days, reference evaporation, soil moisture storage capacity, vegetation type coefficient) are described in Mohan et al. [2018] and Hoogeveen et al. [2015] respectively.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Spatial resolution</th>
<th>Source</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land use map</td>
<td>5 arc min</td>
<td>GMIA version 5</td>
<td>Siebert et al. [2013]</td>
</tr>
<tr>
<td>Groundwater recharge</td>
<td>0.5°</td>
<td>Empirical model</td>
<td>Mohan et al. [2018]</td>
</tr>
<tr>
<td>Irrigation water requirement</td>
<td>5 arc min</td>
<td>GlobWAT model</td>
<td>Hoogeveen et al. [2015]</td>
</tr>
<tr>
<td>Base flow index</td>
<td>0.125°</td>
<td>GSCD version 1.9</td>
<td>Beck et al. [2013]</td>
</tr>
<tr>
<td>Environmental flow requirement</td>
<td>National level</td>
<td>IWMI</td>
<td>Smakhtin et al. [2004]</td>
</tr>
<tr>
<td>(as percentage of runoff)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Food production</td>
<td>National level</td>
<td>FAOSTAT</td>
<td>FAOSTAT [2016]</td>
</tr>
<tr>
<td>Irrigated yield</td>
<td>National level</td>
<td>FAOSTAT</td>
<td>FAOSTAT [2016]</td>
</tr>
<tr>
<td>Irrigation efficiency</td>
<td>National level</td>
<td>AQUASTAT</td>
<td>FAO [2016]</td>
</tr>
</tbody>
</table>
4.4 Results

4.4.1 Non-renewable groundwater abstraction and stress index

The global distribution of long-term average irrigation induced groundwater $SR$ and $NRGA$ are shown in Figures 4.2 and 4.3, respectively. Thirty countries have positive $NRGA$; however, 81% of $NRGA$ is from only 6 countries (India, Pakistan, China, Iran, Turkey and the USA), which indicates that global groundwater depletion is confined to a few regions of the world. These regions consist of the north-eastern parts of the Indian sub-continent (mainly the Indus and Ganga-Brahmaputra basins), the North-western parts of China (mainly the North China Aquifer system and the Song-Liao basin), Western USA (mainly the Northern Great Plain Aquifers, the Ogallala Aquifer and the California Central Valley Aquifer System), the Middle East (mainly the Arabian Aquifer System), and a few areas of Italy and Spain. Overexploitation of groundwater is present in 37% of countries, and moderate to heavily stressed groundwater systems are present in 22% of countries. Most global studies of groundwater problems have not reported stress in any parts of Europe [JS Famiglietti, 2014; Tom Gleeson et al., 2012; Richey et al., 2015; Verma et al., 2004]; however, those studies excluded environmental requirements from groundwater stress assessment. When environmental requirements are considered, high levels of groundwater stress are also discernible in many parts of Spain, Italy, Portugal and France (Figure 4.2 (b)). The mean $NRGA$ reported in this study was in agreement with [Wada et al., 2012a].
Figure 4.2 Mean Groundwater irrigation stress index during 1981-2014 (a) including environmental flow requirements (b) without environmental flow requirements.

Note: Fig. 4.2(a) follows the WSI scale given in Table 4.1 and Fig. 4.2(b) follows the UN renewable stress scale where SR 0 – 0.1: Low stress, 0.1 – 0.4: High stress, 0.4 – 1: Extreme stress and >1: Overexploitation.

Figure 4.3 Mean non-renewable groundwater abstraction from 1981-2014 with percentage of irrigated area with positive deficit of selected countries in boxes.

Note: Negative NRGA indicates water availability is greater than demand, whereas positive NRGA indicates the opposite, and that the system is being exploited.
4.4.2 Non-sustainable food production from groundwater

Country-wise irrigation water requirements met from groundwater were estimated using GlobWAT and evaluated against national irrigation groundwater withdrawal data obtained from FAO. Figure 4.4 (a) shows that the two datasets were highly correlated. Further, recharge estimates from the empirical model were compared against country-wise mean groundwater recharge data from the FAO (Figure 3.11 (a)), and against groundwater recharge estimates from a global hydrological model (Figure 3.11 (b)) [Alcamo et al., 1997; Mohan et al., 2018]. Recharge estimates showed a good correlation with both these datasets.

![Figure 4.4 Scatter between IWR- GlobWAT and IWW-national statistics.](image)

Figure 4.4 Scatter between IWR- GlobWAT and IWW-national statistics.

Figure 4.5 shows the difference between estimated withdrawal under current stress conditions and withdrawal under scenarios where stress is limited to a sustainable level ($SR=0.6$). The negative values (red zone) shows the regions where withdrawal under current condition is higher than that recommended in stress limiting scenarios. India, Pakistan and China were at the forefront in withdrawing more than the recommended level of groundwater for irrigation. Annually, 57.6 million ML of groundwater in excess of the recommended levels are jointly abstracted by these three countries.
Figure 4.5 Change in irrigation water withdrawal (Delta IWR) if SR is set to 0.6 when environmental base flow requirements are included.

Figure 4.6 shows estimates of national food production from non-renewable groundwater under the base case scenario. In this scenario, 89.7% of unsustainable food production is jointly produced by India, Pakistan, China, Iran, Turkey, Spain, the USA and Denmark. Globally, about 450 million tonnes of food are produced from non-renewable groundwater, which is equivalent to the food required to feed a 10th of the world’s population for a year.

Figure 4.6 Unsustainable food production per country from non-renewable groundwater extraction in tonnes (shaded areas), and as a percentage of total food production (circles) if the maximum SR is 0.6.
4.4.3 Groundwater stress remediation

As the above results demonstrate the need of finding a balance between food production and groundwater withdrawal, we examined the degree to which the current status could be improved by increasing irrigation efficiency and productivity. Figure 4.7 shows the percentage change in $SR$ under efficiency improvement scenarios. The map shows 46% and 40% stress reduction due to reduction in volume of water abstraction in high and moderate efficiency scenarios, respectively. When irrigation efficiency was increased to 90% (high case), the number of countries in the overexploitation category was reduced from 39 to 31, and the number of countries with low stress increased from 15 to 27 (Figure 4.8). Aggregated over India, China, Pakistan, Iran and the USA, increasing efficiency to 90% accounted for a reduction of groundwater irrigation abstraction by 26 million ML per year, or 38% of the 2005 $NRGA$ abstraction in these countries.

Figure 4.7 Percentage change in SR in efficiency improvement scenario.
The above-only considered groundwater stress reduction due to improved efficiency and showed that such measures alone could not eliminate stress. Given a future with increasing food demand and decreasing water availability, an approach for improving sustainable food production through a combination of improved efficiency and yield was considered. Under base case scenario (Scenario S1), globally 450 million tonnes of food are produced by overstressing groundwater systems. By increasing global irrigation efficiency to 90% (Scenario S2), 148 million tonnes of food can be produced from previously wasted water. This could reduce unsustainable food production by 44%. In addition to efficiency improvements, if irrigation productivity is also increased to 8 t/ML in the low yield regions (Scenario S3), the same total food production could be achieved from groundwater irrigation with only 89 million tonnes of unsustainable food production globally (i.e., 74% reduction in unsustainable food production) (Figure 4.9). Figure 4.9 also shows the change in food production using non-renewable groundwater under the three scenarios in four major groundwater depletion hotspots. The major increase in sustainable food production was in India where 83 million tonnes (Scenario S2) and 157 million tonnes (Scenario S3) of unsustainable food production became sustainable (National level water savings and reduction in unsustainable food production in the three stress remediation scenarios for the heavily stressed countries is given in Appendix (Table A1)). In addition to the
aforementioned interventions, changes in land use and agricultural practices like reducing the cropping area and switching to less water intensive crop varieties can also reduce the stress on groundwater systems. However, detailed analysis of these changes is out of the scope of this research.

![Figure 4.9 Sustainable and unsustainable food production under different scenarios.](image)

Figure 4.9 Sustainable and unsustainable food production under different scenarios. The blue bars show the unsustainable component of groundwater irrigated food production in 2005 and the amount of that becomes sustainable with higher efficiency and higher yield.

### 4.5 Discussion

Due to increased food demand and the subsequent expansion of irrigated food production, many of the world’s groundwater resources are being overexploited. According to the FAO, the world will need to feed 2 billion extra people by 2030, compared with 2015. This will intensify the stress on groundwater and highlights the need for more improved management of global groundwater resources. A scientific understanding of stress on groundwater systems is essential for managing this resource. This study was carried out with the objective of evaluating stress induced by irrigated food production on groundwater systems. Stress on the system was estimated as a ratio of irrigation water demand and groundwater available for extraction. EBFR was also considered.
Globally, there is an extremely uneven distribution of groundwater stress ranging from $SR<0.1$ to $SR>1$ (Figure 4.2 and Figure 4.3). Groundwater irrigated areas did not always coincide with high yielding aquifers. Currently, the average pumping depth in the irrigated areas of China and India is $>50m$ and is increasing every year making the groundwater irrigation a noneconomic option [Liu et al., 1998; Tushaar Shah, 2009]. It is worth mentioning that countries with high amounts of unsustainable abstraction also have other groundwater irrigated areas with more potential for extracting groundwater. This is particularly so in China and the USA, where some of the major regions of non-renewable groundwater use are located, and where there are other areas in which demand is less than the extraction potential of the system. A spatial rearrangement of food production in these regions could ensure sustainable water availability; however, water is not the only factor in agricultural production, which is also constrained by other factors such as land availability, soil fertility, and climatic conditions. Our results, which identify hot-spot areas of overexploitation, have important implications for national and international governance of water resources, and can help to identify dependence on groundwater thereby informing a more sustainable redistribution of demand.

Considering environmental water requirements when assessing groundwater stress is very important. The results show that exclusion of environmental requirements leads to underestimates of stress in most regions, particularly Europe (Figure 4.2). A very high proportion of rivers in Europe are supported by a high proportion of groundwater baseflow [Smakhtin et al., 2004]. In Mediterranean countries like Spain and Italy, and in parts of the United Kingdom, the groundwater contribution to environmental flow is high due to the large base flow index and high hydraulic connectivity between surface water and groundwater. When the $EBFR$ is deducted from available groundwater, these countries tend to move into the overstressed category. This accentuates the importance of considering $EBFR$ in the assessment, planning and prediction of future groundwater management.

We found that food production in countries like India, Pakistan, the USA, Iran and China placed the greatest stress on groundwater resources. A tenth of the world is fed with food
produced by overstressing groundwater. We found that increased irrigation efficiency alone can save 26 million ML of water which can then either be used to reduce water stress by 46%, or to increase food production by 150 million tonnes while maintaining stress at reasonable levels. Furthermore, if efficiency improvements are reinforced by increased productivity, an additional 249 million tonnes of food can be produced while maintaining the $SR \leq 0.6$. (Figure 4.7, Figure 4.8 and Figure 4.9). One important limitation of the increased irrigation efficiency in S2 and S3 scenarios relates to leaching requirements that are required for maintaining soil health. The required leaching factor is highly site specific and irrigation water quality dependent and requires local data to assess. Here an addition sub scenario (S2a) is considered, in which the irrigation efficiency is limited to 75% of the maximum achievable limit. The 25% water loss is assumed to cater the leaching requirements in more saline areas. The combined information from S2 and S2a gives an indication of the range of irrigation water saving potential.

A combination of management practices like demand-based irrigation scheduling and engineering practices like zero wastage irrigation systems can effectively increase irrigation efficiency. Institutional level strategies like water pricing, water capping and awareness training for end users can also lead to better use of irrigation water and greater productivity [Howell, 2001]. Despite being promising solutions for saving groundwater, these management interventions are difficult to implement in under developed and developing countries due to social, financial, legal and institutional constraints [Elliott et al., 2014; Levidow et al., 2014]. Financial and technological aid to developing and under-developed countries, which are among those experiencing maximum water stress, can greatly improve the health of aquifers.

Despite providing a deeper understanding of current groundwater irrigation stress and analysing possible stress remediation strategies, this study has some underlying assumptions. Due to lack of source-based proportion of water use in conjunctive irrigation areas, 50% of the irrigation in those area was assumed to be from groundwater. In addition, this study does not account for the return flows or inter pixel spatial flows of groundwater and considers
only the rainfall recharge as the source of water available for irrigation. Moreover, the yield statistics per country used in this study is an average of rainfed yield and irrigated yield which could lead to underestimation in rainfed irrigation predominant regions. As this is a global study, the major limitation was with the data quality. Most of the inputs such as irrigation efficiency, food production and area under irrigation were obtained from the FAO and other international institutions. Thus, these data are a compilation of various national and sub-national statistics. Data quality from some national agencies is poor and might have led to some error in estimations for that region. In addition, estimates reported in this study are on a national scale, which means that the effects of spatial variability on agricultural systems within countries that could also have significant effects on stress, could also not been captured.

4.6. Conclusion

This study was carried out with the objective of evaluating stress induced on groundwater systems by irrigated food production. Stress on the system was estimated via the ratio of irrigation water demand to groundwater available for extraction. Unlike previous studies, available groundwater estimates accounted for environmental requirements by subtracting $EBFR$ from natural recharge in the system. Crop specific irrigation water requirements were modelled using the GlobWAT model developed by FAO. The magnitude of groundwater overexploitation was evaluated by quantifying the amount of unsustainable food production for each country. Finally, potential management interventions for remediating groundwater stress without compromising food security were examined by improving irrigation efficiency and increasing irrigation productivity. The scope of this study was restricted to the groundwater irrigated areas of the world.

The analysis showed that ~40% of the total irrigated food producing regions of the world are over exploiting groundwater resources. Accounting for environmental water requirements revealed that food production in some European countries including Spain, Italy and the United Kingdom also resulted in high groundwater stress. Although
groundwater stress is a widespread phenomenon, 81.4% of non-renewable groundwater abstraction is from only 6 countries (India, Pakistan, China, Iran, Turkey and the USA). This non-renewable groundwater abstraction results in the production of 450 million tonnes of food. In other words, a tenth of the world is fed with food produced by overstimulating groundwater. Due to this high dependency on unsustainable food production, reducing groundwater stress by decreasing extraction is not a feasible solution. Therefore, we examined two pathways for remediating groundwater stress: (1) by improving irrigation efficiency and (2) by increasing both productivity and efficiency. We found that increased irrigation efficiency could save 26 million ML of water which can either be used to reduce current stress by 46% (by reducing $NRGA$), or to produce an additional 148 million tonnes of food while maintaining stress at a reasonable level. Furthermore, if efficiency improvement is reinforced by increased productivity, 249 million tonnes of food can be produced without increasing the stress on groundwater. Having said that, achieving these improvements is a major challenge requiring substantial transformation in water management and farming systems for success.
Chapter 5

The Global Groundwater-Food Nexus: Implications of Climate Change

5.1 Abstract

Irrigated food production is the largest consumer of groundwater resources globally. Climate change is likely to impact both supply of, and demand for, groundwater resources, both linked through agricultural production. Despite its importance, little is known about the quantitative relationship between groundwater, food production and climate change at a global scale. This study aims 1) to evaluate stress on groundwater systems due to irrigated food production under two different climate-change scenarios (Representative Concentration Pathway (RCP) 4.5 and 8.5), and 2) to quantify the amount of food produced by over exploiting groundwater under these scenarios. With constant crop area, this study suggests that by 2080 global groundwater irrigation demand would increase in both scenarios by 7% in RCP 4.5 and 6% in RCP 8.5 respectively. This is equivalent to an additional 11 and 4 million ML of irrigation water in RCP 4.5 and 8.5, respectively. In contrast, the sustainable supply of groundwater is estimated to increase by only 3% in both scenarios. This gap between water demand and availability suggests that groundwater stress may increase substantially. In addition, future food demand is expected to increase due to population growth and increased per capita calorie demand. If the irrigated area remains constant and the food demand increases in proportion to the population growth, by 2080, 25% (RCP 4.5) and 20% (RCP 8.5) of total food produced from groundwater will be produced by over exploiting groundwater. This is equivalent to an additional 112 (RCP 4.5) and 90 (RCP 8.5) million tonnes of food per year produced by overstressing groundwater resources. This study suggests that climate change will add to the already significant challenge of transitioning to sustainable groundwater management while maintaining food
production to meet the world’s requirements and highlights the necessity for significant climate change adaptation.

5.2 Introduction

Global food requirement has increased by 70% over the last century, and the challenge of feeding an additional 2 billion people by 2030 is further intensifying pressure on irrigated agriculture [FAO, 2009]. Consequently, stress on water resources is increasing, particularly stress on groundwater systems which provide approximately 60% of global irrigation water. Due to rapidly increasing global population and associated increases in food demand, groundwater extraction has increased by a factor of approximately 6 in the last few decades. In arid and semi-arid regions where groundwater recharge is low and irrigation water requirements are high, this has led to progressive depletion of underlying aquifers [Siebert et al., 2013]. In many parts of the world, drought events have substantially impacted surface water availability, leading to increasing exploitation of groundwater resources. In general, the magnitude of stress on groundwater systems globally is increasing every year and this is expected to continue in the future as a result of rising demand and changing climate [Richard G Taylor et al., 2013].

The links between groundwater stress and groundwater irrigated food production will be further complicated in the future by changing climate. While climate has changed frequently in the past [Dragoni and Sukhija, 2008], these changes are currently happening over much shorter time scales. Measurements of global CO2 concentration, one of the primary climate regulators, show an exponential increase from the industrial revolution (post 1760s) [Green et al., 2011; Petit et al., 1999]. This accelerated rate of change will affect water resources in a variety of ways [Dragoni and Sukhija, 2008; Green et al., 2011; Richard G. Taylor et al., 2012]. Compared with surface water, less attention has been given to studying climate change impacts on groundwater. Climate change can affect groundwater resources in several potential ways, either directly or indirectly [Richard G Taylor et al., 2013]. Changing climate can directly impact groundwater resources by altering the various components of
Chapter 5 The Global Groundwater-food Nexus: Implications of Climate Change

groundwater systems such as recharge and discharge. Indirect impacts include variations in natural (i.e., water use by natural vegetation) and anthropogenic (i.e., irrigation, industrial and domestic) demands on groundwater resources. Climate and population driven increases in irrigation demand and the subsequent shift to greater use of groundwater for irrigation has resulted in lowering of groundwater tables to an unsustainable level in many parts of the world [Liu et al., 1998; Llamas and Martinez-Santos, 2005; Tushaar Shah, 2009; T Shah et al., 2004]. Eventually, the drop in the water table adversely affects groundwater dependent food production. Thus, a feedback loop is formed. Despite indirect impacts being dominant, little is known about the complex relationship between climate change, groundwater stress and groundwater irrigated food production [Alderwish and Al-Eryani, 1999; J Chen, 2010]. Sophocleous [2004] suggests that less attention has been given to studying the impact climate change on groundwater systems because they respond more slowly to climate change compared to surface water. However, in recent decades researchers and policymakers have recognized the importance of scientifically evaluating the impact of climate change on groundwater resources [Bear et al., 1999; Zektser and Loaiciga, 1993].

In this study we aim to predict 1) future stresses on groundwater systems under changing climate and 2) the amount of future food production likely to be supported by overexploitation of groundwater resources. The primary focus of this paper will be to evaluate the cumulative direct and indirect climate change impacts on groundwater resources due to variations in groundwater recharge and irrigation water requirements. The later part of the paper also estimates changes in unsustainable food production through unsustainable groundwater exploitation due to changes in climate and food demand over the next 100 years. In order to accomplish these objectives, we forced a global groundwater recharge model (developed in Chapter 3) and a global water balance model (GlobWat; [Hoogeveen et al., 2015] with General Circulation Model (GCM) outputs from phase 5 of the Coupled Model Intercomparison Project (CMIP5). The Hadley Centre Global Environmental Model version 2 Earth Systems model - (HadGEM2 -ES) was chosen for this study [Collins et al., 2011; Jones et al., 2011]. This study was carried used climate simulations from 2006 to 2100 under two different Representative Concentration Pathways (RCP); RCP 4.5 and RCP 8.5.
To better understand changes in climate prediction due to internal variability in the HadGEM-ES we use three initial condition ensembles for each RCP. Detailed characteristics and the justification for choosing the RCPs are given in the following section.

5.3 Methods

5.3.1 Groundwater stress estimation

Stress on groundwater resources was assessed using the stress estimation definitions in Chapter 4. In order to estimate stress two factors were calculated, 1) non-renewable groundwater abstraction (NRGA) and 2) a Groundwater stress index (GSI). NRGA was defined as the water demand met from groundwater in excess of availability (Eq. 5.1). Here water demand is the irrigation water requirement (IWR) met from groundwater, and water availability is estimated with diffuse natural groundwater recharge in excess of environmental base flow requirements (EBFR). The IWR was estimated at a spatial resolution of 5 arc min by forcing GlobWAT [Hoogeveen et al., 2015] with future climate data, whereas groundwater recharge was estimated by running an empirical global recharge model [Mohan et al., 2018] at a 0.5° spatial resolution. Further analysis was carried out at 0.5° resolution by upscaling the IWR data. The stress in the system due to irrigation was assessed by calculating the groundwater stress index (GSI). GSI is defined as the ratio between use and availability (Eq. 5.2), which is quite similar to the UN Commission on Sustainable Development Scarcity Index [Raskin et al., 1997]. GSI was a normalized form of the groundwater status in a given area and enabled comparisons of stress levels across different scales. The present stress analysis using the GSI was carried out for two different climate scenarios viz., RCP 4.5 and 8.5, by forcing the above-mentioned models with outputs from three ensembles of the Global Climate Model HadGEM2-ES. A detailed description of the HadGEM2-ES and the climate scenarios will be provided in session 5.3.3.

\[ NRGA = IWR - (R - EBFR) \]  

[5.1]
\[GSI = \frac{Water\ Withdrawal}{Water\ Availability} = \frac{IWR}{\varepsilon(R-EBFR)}\]  

Where;  
NRGA = Non-renewable groundwater abstraction, mm/y  
GSI = Groundwater stress index  
IWR = Irrigation water requirement met from groundwater, mm/y  
R = Groundwater recharge, mm/y  
EBFR = Environmental baseflow requirement, mm/y  
\(\varepsilon\) = Irrigation efficiency calculated at country level

This study considers only groundwater irrigated areas. Groundwater irrigated areas were identified using the Food and Agricultural Organization-AQUASTAT land use map. Land use data for 2005 were compiled and downscaled from various national and subnational agencies [FAO, 2016]. In this study we assumed that the current area under irrigation remained constant into the future. This was due to a lack of adequate data on which to base estimates of future change. This study considered both groundwater irrigated and conjunctive use areas. Due to data limitations, the conjunctive use areas were considered to be 50% groundwater irrigated.

5.3.2 Unsustainable food production

Unsustainable food production from groundwater was estimated at the country level. Unsustainable food production was defined as any food production resulting in WSI \geq 0.6. This definition follows Smakhtin [2004] who categorized WSI \geq 0.6 as indicative of heavy exploitation. Future unsustainable food production based on groundwater exploitation was estimated by considering two demand scenarios 1) constant demand scenario: where current food demand remained constant in the future and 2) varying demand scenario: where future food demand varied in response to population change. Current food production was obtained from FAOSTAT [FAOSTAT, 2016] and in the constant demand scenario, total food production was calculated as the sum of total cereal, pulses, root crop, fruits, tree nuts and
vegetables per country and assumed to remain constant until 2100. In the varying demand scenario, potential change in food demand per country for 2030 and 2050 was obtained from IMPACT model results. IMPACT is the International Model for Policy Analysis of Agricultural Commodities and Trade developed by the International Food Policy Research Institute (IFPRI) \cite{IFPRI,2017}. This was extrapolated to calculate food demand in 2080 assuming a linear trend. The IMPACT model simulates the operation of national and international markets, solving for production, demand, and prices that equate to supply and demand across the globe. Future change in food demand is estimated as a function of commodity price and the price of competing commodities. In order to incorporating varying demand into calculation of unsustainable food production, irrigation water withdrawal per country was increased/decreased in proportion to the projected change in food demand in 2020, 2050 and 2080. Essentially this assumes a constant share of food production between rainfed, surface irrigation and groundwater irrigation.

5.3.3 Climate change analysis

5.3.3.1 GCM data sources and pre-processing

The climate change impact on groundwater stress due to irrigated food production was modelled by forcing the GlobWAT model and the Recharge model with the General Circulation Model (GCM) outputs from phase 5 of a selected Coupled Model Intercomparison Project (CMIP5) GCM. The Hadley Centre Global Environmental Model version 2 Earth Systems model - (HadGEM2 -ES) developed by the Met Office Hadley Centre was the GCM chosen for this study \cite{Collins et al.,2011,Jones et al.,2011}. The choice of GCM was based on rankings by McSweeney et al. \cite{2015} and T McMahon et al. \cite{2015} for the best globally performing GCMs in CMIP 4 and 5. HadGEM2-ES is a coupled atmosphere/land and ocean model with spatial resolution of $1.875^\circ \times 1.25^\circ$ and runs at a timestep of 30 minutes.

For this study, monthly historical model outputs (1960 – 2005) and future predictions (2006-2100) were downloaded using the KNMI Climate Explorer
Chapter 5 The Global Groundwater-food Nexus: Implications of Climate Change

(http://climexp.knmi.nl/start.cgi). Monthly mean precipitation and inputs required to calculate potential evapotranspiration using the Penman Monteith equation (viz., Minimum and maximum temperature, relative humidity, atmospheric pressure, short and longwave radiation and wind speed) were extracted from CMIP5 HadGEM2-ES simulations. In order to incorporate uncertainty due to internal variability in GCM predictions, three initial condition ensembles were chosen [Jones et al., 2011]. Raw data obtained from Climate Explorer was bias corrected and downscaled against high-resolution gridded CRU data (https://crudata.uea.ac.uk/cru/data/hrg/) using quantile-quantile bias correction techniques (QQ bias correction - [Themeßl et al., 2012]). In this study pixel-by-pixel correction was done by calibrating the correction algorithm from Jan/1960 to Dec/2002. In order to account for different possible future emission scenarios, two Representative Concentration Pathways (RCP); RCP 4.5 and RCP 8.5 were used.

5.3.3.2 RCP scenario description

In their Fifth Assessment Report (AR5) the Intergovernmental Panel on Climate Change (IPCC) proposed a new set of emission scenarios considering different possible future changes to factors contributing to global warming. These new scenarios are called Representative Concentration Pathways (RCPs). There are four pathways: RCP8.5, RCP6, RCP4.5 and RCP2.6. Two of the four pathways, RCP 4.5 and RCP 8.5, were chosen for this study. RCP 8.5, the high emission scenario was developed using the MESSAGE model and the IIASA Integrated Assessment Framework, and is characterized by increasing greenhouse emissions over time [Riahi et al., 2011]. In contrast, RCP 4.5 which was developed by the Global Change Assessment Model (GCAM) team at the Pacific Northwest National Laboratory’s Joint Global Change Research Institute (JGCRI), leads to emission stabilization after 2100 [Thomson et al., 2011]. Detailed characteristics of RCP 4.5 and 8.5 are given in Table 5.1.
Table 5.1 Characteristics of RCP 4.5 and RCP 8.5

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>RCP 4.5</th>
<th>RCP 8.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiative forcing</td>
<td>4.5 Wm² post 2100 (~650 ppm of CO₂ equivalent)</td>
<td>8.5 Wm² in 2100 (~1370 ppm of CO₂ equivalent)</td>
</tr>
<tr>
<td>Greenhouse gas emission</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Temperature anomaly by 2100</td>
<td>2.4°C</td>
<td>4.9°C</td>
</tr>
<tr>
<td>Population by 2100</td>
<td>~7000 million</td>
<td>~12000 million</td>
</tr>
<tr>
<td>Energy and oil consumption</td>
<td>750 EJ (double the current consumption)</td>
<td>1600 EJ (very high due to population growth and lower technological development)</td>
</tr>
<tr>
<td>Land use</td>
<td>Cropland and pasture decrease, forest cover increases</td>
<td>Cropland and pasture increases</td>
</tr>
<tr>
<td>Air pollution</td>
<td>Medium</td>
<td>Medium - high</td>
</tr>
</tbody>
</table>

5.4 Results

5.4.1 Direct climate change impact on groundwater systems: Global groundwater recharge

In the next 100 years both RCP 4.5 and 8.5 climate change scenarios would lead to increases in mean diffuse recharge in groundwater irrigated areas of the world (Figure 5.1). Globally, in groundwater irrigated areas, there is approximately 3% increase in mean recharge by 2080. By the end of the next century mean groundwater recharge in global groundwater irrigated areas will be 241 mm/y. Global groundwater recharge peaks around 2070 (both RCPs) and stabilizes thereafter. Comparing the three ensembles shows a marked difference in predicted groundwater recharge. The shaded regions around the solid lines in Figure 5.1 represent the range in predictions of the three ensembles. There is 5 to 10 mm/y variation in recharge predicted using the different model ensembles. Nevertheless, overall trends for
annual mean recharge estimates were similar in all ensembles. More surprisingly, they were also similar under the two different RCPs. The two different RCPs follow similar temporal patterns, especially after 2060. This is largely due to the cancelling out of fluctuations in recharge in spatial trends. Regional differences in predicted recharge are evident in Figure 5.2 which shows proportional change in future groundwater availability.

The spatial pattern of proportional change in groundwater available for irrigation from 2020 to 2080 is shown in Figure 5.2. Results suggest that groundwater availability will increase in some regions that are currently stressed such as the North China Plain and South India. Groundwater availability is expected to increase by around 20 to 40% in the North China plain under both RCPs, whereas in South India the expected change varies with scenario. On the other hand, by 2080 the Indo Gangetic region in North India, which is another hotspot of groundwater exploitation, is expected to experience reductions in groundwater recharge of 30 to 50% and 10 to 15% under RCPs 4.5 and 8.5, respectively. As land use land cover (LULC) was assumed to remain constant in this study, the effects of climate change effect on groundwater recharge are essentially due to changes in precipitation and potential evapotranspiration. Of the two, precipitation is the more sensitive parameter in the recharge model [Mohan et al., 2018], and is therefore likely to have the greatest impact on recharge.

![Figure 5.1 Temporal change in mean annual groundwater recharge in groundwater irrigated areas under RCP 4.5 and 8.5 (the shaded regions around the solid lines show the range of predictions by different ensembles of HadGEM2-ES at a time step).](image)
5.4.2 Indirect climate change impact on groundwater systems: Global groundwater irrigation water requirement (IWR)

As irrigated food production is the largest consumer of groundwater globally, one of the primary indirect impacts of climate change on groundwater resources will be variations in irrigation water requirement (IWR). According to our results, global IWR in groundwater irrigated areas will increase under both the climate scenarios (Figure 5.3). By 2080, global IWR will reach 169 and 166 mm/y under RCP 4.5 and 8.5, respectively, representing 7% and 6% increases from estimates of current global groundwater irrigation demand in the respective scenarios. Projected increases in IWR will be greater in low- and medium-income countries (LMIC) than wealthier countries due to the spatial patterns of change in climatic variables. By 2080 IWR in LMICs is expected to increase by 6.1% and 6.5% under RCP 4.5 and 8.5, respectively. In contrast, in high income countries, IWR is expected to increase by only 3.9% in RCP 4.5 and 3.4% in RCP 8.5. One of the most concerning findings from this analysis was the pattern of regional increase in IWR (Figure 5.4). IWR is increasing more strongly in regions where groundwater is heavily overexploited like the North China Plain, North India and Central USA. Particularly significant increases in IWR are projected by
2080 in China (+10.3% in RCP 4.5 and +11.5% in RCP 8.5), India (+8.9% in RCP 4.5 and +9.3% in RCP 8.5), Pakistan (+17.2% in RCP 4.5 and +0.18% in RCP 8.5) and USA (+10.5% in RCP 4.5 and +9.1% in RCP 8.5).

Figure 5.3 Temporal change in mean annual irrigation water requirement (IWR) in groundwater irrigated areas under RCP 4.5 and 8.5 (the shaded regions around the solid lines show the spread of prediction by different ensembles of HadGEM2-ES at a time step).

5.4.3 Future groundwater irrigation stress and associated unsustainable food production

If groundwater irrigated area remains unchanged in the future, increase in future irrigation water requirement (+7%) is higher than increase in future groundwater availability for irrigation (+3%), implying that groundwater stress is most likely to increase in the future. Heavily groundwater dependent irrigated regions like North-West India, South-East China, a few parts of USA, Spain, Portugal, France and Italy will experience increased groundwater stress under both scenarios (Figure 5.5). In the North western region of the Indian peninsula, groundwater stress due to irrigation is projected to increase by 27% and 60% under RCP 4.5 and 8.5 respectively. In most places stress is greater under RCP 4.5 than RCP 8.5 (Figure 5.5) which is most possibly the result of greater IWR in RCP 4.5 compared to 8.5 (Figure 5.3). The evidences from this study clearly shows that despite increases in groundwater
recharge, climate change will increase the stress on global groundwater systems. On average, the area of groundwater irrigation in the heavily stressed category ($WSI \geq 0.6$) is expected to increase by approximately 100 million ha in both the scenarios.

Figure 5.4 Percentage change in irrigation water requirement (IWR) in groundwater irrigated areas from 2020 to 2080 under climate change scenario (a) RCP 4.5 and (b) RCP 8.5 (negative values indicate decreased water availability and positive values indicate increased water availability). The results are the average of three ensembles.

Future stress on groundwater systems is directly related to unsustainable food production. Unsustainable food production was calculated based on the scenarios defined in section 5.3.2. Unsustainable food production under constant demand conditions was due to the effect of climate change alone, whereas, with conditions of varying demand both climate change and
anthropogenic influences contributed. A varying demand scenario is more realistic, and this study is more interested in the combined effect, further results will be presented based on varying demand scenario. Under conditions of varying demand, by 2080 global increases in unsustainable food production were predicted to be 25±5% and 20±10% for RCP 4.5 and 8.5, respectively (Figure 5.6). This is equivalent to an additional 112 and 90 million tonnes of food production overstressing groundwater systems every year in respective RCPs. Globally, combined increases in unsustainable food production due to both climate and anthropogenic influences were substantially more than increases due to climate change alone. Trends in unsustainable food production were highly region specific, with India, Pakistan and Bangladesh having the largest increases by 2080. Approximately 90% of total unsustainable food production was from 7 countries (India, Pakistan, China, Bangladesh, Turkey, Iran and Egypt) which clearly depicts the heterogeneity in distribution of groundwater stress.

5.5 Discussion

The results presented in section 5.4.1 clearly depict future increases in groundwater availability. The inputs to the groundwater recharge model used in this study are precipitation, PET and LULC. LULC is assumed constant into the future. Also, the model is more sensitive to precipitation than PET. Therefore, global increases in water availability reflect increased precipitation. However, future increases in precipitation mostly focus on the wetter regions of the planet, which do not always coincide with heavily groundwater irrigated areas. Moreover, results from this study only account for changes in the quantity of available water, not its quality, which is not always suitable for irrigation. Several studies have reported deterioration in groundwater quality over various parts of the world [Alderwish and Al-Eryani, 1999; J S Famiglietti, 2014; Kundzewicz and Doell, 2009]. Thus, this increase in water availability does not necessarily decrease groundwater stress.
Figure 5.5 Proportional change in Groundwater Stress Index (GSI) from 2020 to 2080 under a) RCP 4.5 and b) RCP 8.5 (assuming constant groundwater irrigated area). Note: positive values indicate increases in GSI and negative values indicate decreases in GSI.
Increased irrigation demand due to climate change and population explosion also plays a key role in determining future groundwater stress. Future increases in temperature and other evaporative forcing variables, and changes in climate are likely to influence the...
evapotranspiration of plants. While variations in precipitation affect the water deficit that irrigation must make up. As this study uses GCM data to capture climate change signals, trends in IWR results are predominantly due to the changes in temperature and precipitation and do not reflect micro climate influences. The results show an increase in IWR throughout the next century. This increase might be a combined effect of temperature, rainfall, wind and radiation changes. The main factor controlling future temperature is atmospheric CO₂ concentrations. Elevated atmospheric CO₂ concentration can have contrasting effects on plant physiology, for example, increased water requirements due to intensification of leaf area index [Anten et al., 2004; Hartz-Rubin and DeLucia, 2001] and reduction in evapotranspiration due to stomata closure. [Shahid, 2011]. However, the effect of temperature and CO₂ concentrations on irrigation water requirement are difficult to generalize as both are highly influenced by plant physiology. Another important point is that the increase in IWR was concentrated mostly in low and medium income countries (LMIC) where the projected population growth is high. Economic growth in LMICs will pave the way for changes in dietary preferences which could change future agricultural water demand. The areas most likely to experience increases in IWR identified in this study (Figure 5.4, yellow to red region) coincided with regions identified by Tom Gleeson et al. [2012] as most likely to experience increases in dietary calories. Therefore, the impact of climate change on IWR in LMICs is a combined result from both climate change and population explosion.

Furthermore, increases in groundwater availability is offset by increases in irrigation water demand met from groundwater. Globally, the availability of and demand for groundwater in the future are increasing simultaneously imposing constant stress on all major aquifers. Heavily groundwater dependent irrigated areas like the Indo Gangetic basin, North China Plain, Spain, Central US and France are expected to have a 30 to 60% increase in groundwater stress by 2080. The immediate repercussions of this will be seen in groundwater related food production. The effects of climate change on food security will be unevenly distributed geographically. As discussed previously, economically developing countries such as India, Pakistan and Bangladesh will be affected more. The inability of economically backward countries to adapt to climate change will increase the gap between production and
demand in those countries. The increase in unsustainable production will also possible increase food pricing in the future. Due to the decrease in water levels in many regions such as India and China, groundwater pumping has become uneconomical without government subsidies. This increase in production costs will be reflected in agricultural commodity pricing. Therefore, the impact of climate change on the groundwater stress in heavily groundwater dependent irrigated areas will have significant economic implications for the food production of these regions.

Despite giving a quantitative picture about the future global groundwater stress, this study has some limitations. Firstly, several influences on groundwater recharge remain unaccounted (Ref. Chapter 3 for more details). Secondly, future global warming will have a significant impact on snow and glacial melt, resulting in increased streamflow in glacial/snow fed rivers, and subsequently increasing groundwater recharge in hydraulically connected regions, followed by declines a snow and ice contract. However, the timing, intensity and spatio-temporal distribution of snow and ice melt are still uncertain, and the recharge model used only accounts for pluvial recharge. Therefore, the aggregated effect on groundwater available for recharge is still a future research challenge. In addition, there is evidence that mountain valley aquifers are exhibiting shifts in seasonal groundwater level fluctuations due to earlier spring snow melts [Allen et al., 2010]. This will reduce summer streamflow and which will be further aggravated by low groundwater levels [Richard G Taylor et al., 2013]. This in turn reduces surface water availability for domestic, agricultural and industrial needs and may eventually increase stress on groundwater systems.

5.6 Conclusion

This study evaluated the nexus between groundwater depletion, groundwater dependent food production and climate change. The direct impact of climate change on groundwater resources was mainly due to altered groundwater recharge and hence availability of groundwater for extraction. Indirect impacts of climate change resulted from changes in IWR and food demand. Both groundwater availability and groundwater demand will increase in
the future, with the increase of demand outweighing the increase of availability. Thus, significant stress on groundwater systems will increase under both climate change scenarios. The major conclusions from this study are:

- Groundwater stress due to irrigated food production is concentrated in a few heavily irrigated regions such as North China Plain, Central USA, North west India, Pakistan and Bangladesh.

- Groundwater stress and unsustainable food production are expected to increase more in LMICs than in economically developed countries.

- Globally, additional 112 and 90 million tonnes of food will be produced by overstressing groundwater systems every year in RCP 4.5 and 8.5 respectively.

- The percentage increase in global unsustainable food production due to combined anthropogenic and climate change effects is 16 ± 6% and 23 ± 4% (RCP 4.5 and 8.5, respectively), which is more than climate change alone.

The sustainable food production to meet the growing demand under climate change is a real challenge. This study quantified the groundwater challenge and add to understanding which reinforces this challenge. In order to produce food sustainably, efficient climate change adaptation techniques must be adopted in order to make the best possible use of all available resources, particularly water. Results from this study will also aid in identifying hotspots of groundwater stress.
Chapter 6

Discussion and Conclusions

The final chapter starts with a summary of the results chapters (section 6.1) which is followed by a discussion of the key contributions and implications of the results in sections 6.2 and 6.3 respectively. The assumptions and limitations of the study are summarized in section 6.4. Section 6.5 discusses the future research directions, with conclusions given in section 6.6.

6.1 Summary

There exists limited knowledge of the quantitative relationship between global groundwater depletion and groundwater dependent agriculture. This study aimed to investigate the relationship between groundwater depletion and groundwater dependent agriculture, particularly food production, at a global scale. This study was carried out in three phases: 1) developing a groundwater recharge model to estimate the global groundwater potential, 2) evaluating the current groundwater stress due to food production and 3) predicting the future groundwater stress under different climate change scenarios. The key results were presented as three journal papers (Chapters 3, 4, and 5), which address the three objectives of this study (see the Chapter 1 - Introduction).

In the first results chapter (Chapter 3) an empirical global groundwater recharge model was developed by identifying all the major factors that have influence on groundwater recharge. Recharge estimates reported in the literature from various parts of the world (715 sites) were compiled and used to develop and test the model. Unlike conventional recharge estimates from water balance models, this study used a multi-model inference approach and information theory to explain the relationship between groundwater recharge and various influential factors to predict groundwater recharge at $0.5^0$ resolution. The recharge estimates presented in this chapter are unique and have been tested with an extensive validation carried
Chapter 6 Discussion and Conclusion

out using both independent local estimates and national statistics from the Food and Agriculture Organization (FAO). Thus, they are more thoroughly tested than the existing global groundwater recharge estimates. The recharge model developed in Chapter 3 was then used in Chapter 4 to estimate the global groundwater extraction potential for irrigated food production.

Chapter 4 addressed the second research question which focuses primarily on determining the stress on groundwater systems resulting from irrigated food production. The stress on groundwater systems was analysed using the ratio of water use to water availability, allowing for environmental requirements. The groundwater extraction potential or groundwater availability was determined using the recharge model developed in this study and described in Chapter 3 and the irrigation water demand by running a global water balance model called GlobWAT. In addition to the global stress estimation, the unsustainable food production from groundwater resources on a country level was estimated using the national level production statistics. This chapter also explored various pathways for stress reduction by improving irrigation efficiency and increasing productivity. Most of the data for this analysis were from modelling or international agencies like the FAO (Food and Agriculture Organization). According to the results, about one third of all areas with groundwater irrigation are overexploiting groundwater resources and every year 450 million tonnes of food production rely on excessive groundwater extraction. Increasing irrigation efficiency and irrigation productivity could significantly reduce but not eliminate groundwater stress. For example, raising efficiency to 90% and crop water productivity to >8 t/ML could reduce the unsustainable food production by 74%.

The third results chapter (Chapter 5) is devoted to evaluating groundwater stress under future climate change and food requirement scenarios. This chapter mainly intends to 1) evaluate the stress on the groundwater systems due to irrigated food production under changing climate and 2) to quantify the food produced unsustainably by overexploiting groundwater resources under future climate change. In order to accomplish these objectives of this chapter, the global groundwater recharge model and GlobWAT were run with General
Circulation Model (GCM) outputs from the phase 5 of the Coupled Model Intercomparison Project (CMIP5). This part of the study was carried out from 2006 to 2100 for two different Representative Concentration Pathways (RCP) viz. RCP 4.5 and RCP 8.5. The results project that in the coming century, global groundwater irrigation demand would increase by 7% and 6% in RCP 4.5 and 8.5 respectively. Considering fixed groundwater irrigated area, by 2080, 25% (RCP 4.5) and 20% (RCP 8.5) of the total food produced from groundwater will be produced by over exploiting the groundwater which is equivalent to an additional 112 and 90 million tonnes of food are produced every year by overstressing groundwater water in respective RCPs.

6.2 Key Contributions

This research has quantified the relationship between groundwater stress and dependent food production at the global scale. By focusing on groundwater, it complements similar studies that have addressed this question for surface water, which has not been considered previously. The major academic contributions from this study by addressing the knowledge gaps identified in Chapter 2 (Section 2.5) are as follows.

- It developed an empirical recharge model by identifying the major factors having control over recharge. The recharge estimates from this model complement earlier estimates by taking an empirical approach. They show good comparison with the recharge estimates from the existing global hydrological models, however, are more reliable than the existing ones due to the extensive tests done at different spatial scales. This model provides easy and reliable initial estimates of diffuse recharge for any area of interest outside areas with significant freezing, as this model requires only precipitation, PET and land use as the input. The developed empirical model can be easily integrated with existing hydrological models to improve the groundwater representation. The model development method proposed in this study can be used to develop empirical recharge model at any spatial scale provided adequate data availability.
The study quantified the global groundwater stress due to irrigated agriculture and estimated the annual unsustainable food production by country. The major groundwater stress areas are identified, and this will help in focusing the managerial interventions in these areas for addressing the global groundwater stress challenge. Areas of major stress include the North China Plain, the High Plains Aquifer of USA, North west India and Pakistan, in agreement with several other groundwater studies. However, this study also identified some parts of Europe as groundwater stressed which have not generally been reported as stressed previously. This relates to the environmental baseflow requirement, which is strict in these regions. In addition, this study demonstrated the potential role of managerial interventions like irrigation efficiency improvement and irrigation productivity increase in reducing groundwater stress.

It redefined the existing groundwater stress concept by including the Environmental Base Flow Requirement (EBFR) from groundwater in the analysis. Exclusion of EBFR underestimates the stress in regions with high hydraulic conductivity. This drew on the surface water stress indicator developed by Integrated Monitoring Initiative (coordinated by UN-Water). For instance, the results from this study show large increase in the stress in certain regions of Europe like Spain, Italy and United Kingdom when environment flow is considered in the stress analysis. As noted above, these areas were not previously reported to be stressed either from a surface water or groundwater perspective.

The research evaluated the climate change impact on groundwater stress and associated food production in the future. The change in stress in 2020, 2050 and 2080 was estimated for two climate change scenarios; RCP 4.5 and 8.5. Unlike existing research, this study accounted for the internal variability within the GCM by using different ensembles for the same GCM. The direct and indirect
impact of climate change on groundwater resources depicted in this study generally follows similar trend as the impacts on surface water reported in previous studies. The hydrological response to climate change of both surface and groundwater were particularly similar in tropical and mid-latitude basins.

6.3 Implications and Applications

The major implications and applications of the results from this research are given as follows.

- **Evidence-based groundwater management**: One of the critical decisions to make while managing the groundwater resources is the safe extractable limits of the aquifer. The safe extractable limits or in other words the groundwater development potential is primarily governed by what is going into the system as groundwater recharge. The recharge model developed in this study can help to quantify the groundwater extraction potential all over the world. Additionally, the stress map developed helps to identify the zones with major stress and to design site-specific management schemes to rejuvenate those areas. The stress maps also show some low stress areas for which groundwater development potential could be investigated in more detail.

- **Groundwater-surface water integrated management**: Most existing studies assessing water stress or scarcity focus on only the surface water resources and in most cases the solution for stress reduction is to switch to an alternative water supply like groundwater. However, the over stressed regions identified in this study (North west India, Pakistan, North China, Central USA and Iran) mostly coincide with the surface water stressed areas identified in earlier studies. This means, switching the irrigation source from surface water to groundwater is not going to relieve the water stress in those regions. Moreover, under future climate change the surface water resources will be more vulnerable to extreme events and the repercussions of this
will impact on the groundwater as well. Therefore, the results from this study provide a basis for integrated management of both water resources under climate change.

- **Policy making by international agencies**: As most of the major aquifers are transboundary aquifers, the managerial decisions are not always constrained to national level. In managing these transboundary aquifers international agencies like Food and Agricultural Organization (FAO) and International Water Management Institute (IWMI) play a key role. As this research covers all the groundwater irrigated areas of the world, the results will assist in making decisions on aquifers shared across political boundaries. In addition to this, the results can enhance the databases of these agencies and can be used either to expand the research potential or to increase the awareness about the groundwater status and its consequences.

- **Future prediction of food pricing and commodity availability**: The last part of this study quantified the increase in unsustainable food production from groundwater in the future. Due to the reducing groundwater level in many regions like India and China, the cost of groundwater pumping is increasing, this information could contribute to predicting the future changes in food prices.

### 6.4 Limitations and Assumptions

A groundwater study of this scale is not possible without certain assumptions. The assumptions and limitations of each individual research question is included in the corresponding chapters. This section gives a broader overview of the assumptions and limitations of the thesis as a whole:

1. **Data availability**: One of the major factors limiting the groundwater water research at a large scale is the availability of data. Unlike surface water resources, there is not an extensive monitoring network for groundwater. There are no gridded measurements of any of the physical groundwater characteristics available for
regional scales or above. The recharge estimates used in Chapter 3 to develop the groundwater recharge model were collected from the literature and were measured using different measurement techniques and at different temporal and spatial resolution. The discrepancies in the scale of the recharge samples used to build the model and the scale of predictors used also contribute to some error in the final predictions. The model was developed with an assumption that these differences will not have significant effect on the preciseness of recharge measurement and model residual analysis supported this assumption. Other key limitations with this analysis are that only diffuse recharge was considered (no fluvial recharge was considered) and return flow under irrigation was not considered. These limitations could systematically underestimate recharge and, hence, have a systematic impact on results. In addition, regions with significant freezing like Northern Russia, Canada and Greenland were ignored due to lack of adequate recharge observations, although there is generally little irrigation in these regions. In the latter parts of the thesis (Chapter 4 and 5), the analysis was confined to the groundwater stress in terms of quantity. The quality degradation like salinity problems due to excessive irrigation was not considered. In addition, 50% of the irrigation in the conjunctive irrigation areas was assumed to be from groundwater in Chapters 4 and 5 as there were no data available on the source-based proportion of water use in these areas. Additionally, the crop yield and irrigation efficiency used in Chapter 4 and 5 are country level averages. Generally, both efficiency and productivity are higher for groundwater irrigated areas that those with canal irrigation, and the averaging may slightly overestimate the stress on the system.

2. **Data quality**: The quality of data available was also a major challenge for this study. Most of the data used in Chapter 4 and 5 such as irrigation efficiency, food production and irrigation area were obtained from a range of sources like the FAO and other international institutions. These data were a compilation of various national and sub-national statistics. The data estimation and reporting capacities of national agencies vary significantly and raise concerns about the accuracy of the data. In
addition, according to FAO AQUASTAT reports, most national institutions in
developing countries prioritize subnational level statistics over national level
statistics, and in most cases, data were not available for all sub national entities. This
decreases the accuracy of country wide averages and raises concerns about the
reliability of using them as standard comparison measure. Data quality from some
national agencies is poor and might have led to some error in estimations for that
region. Moreover, the major areas of groundwater stress are in middle- or lower-
income countries where the data compilation capability is highly financially
constrained.

3. Changes in land cover and land use: Another limitation of this study is the possible
changes in land use and land cover (LULC). Due to lack of both historic LULC and
future LULC scenarios, the LULC of 2005 was assumed for both the past and future,
which is unlikely to be the case in reality. This assumption introduces additional
uncertainty in the future stress projection made in this study.

4. Concept simplification: This study covered all the groundwater irrigated areas of
the world. In order to include the large spatial range, the impact of complexity and
heterogeneity of the groundwater aquifers were assumed to be insignificant and was
ignored in the study. Certain groundwater characteristics like exfiltration,
preferential flow, lateral flow and cone of depression which are important at a finer
resolution were not considered in this study. Moreover, this study was based on a
single layered unconfined aquifer system. In reality, aquifer systems can be confined
and even multi layered. In addition, this study did not account for the return flows or
regional flows of groundwater between grid cells and considered only the rainfall
recharge as the source of water available for irrigation.

5. Simplification of base flow index and base flow dependent ecosystem: Chapter
4 uses the base flow separation concept to calculate the EBFR. In steeper regions,
base flow is likely to account for most of the environmental water requirement that
depends on groundwater. In flat regions, other ecosystems such as wetlands and terrestrial vegetation may account for most of the environmental use of groundwater. This simplification adds to uncertainty in the estimated environmental water requirement that depends on groundwater.

6. **Uncertainty in future climate**: The entire analysis in Chapter 5 assumes that the future climate is going to follow the Representative Concentration Pathways (RCPs) proposed by Intergovernmental Panel on Climate Change (IPCC) in their Fifth Assessment Report (AR5). This may not be true. There is a high level of uncertainty involved in the climate predictions which will be reflected in the results as well. Moreover, the recharge model calibrated with past data was used in Chapter 5 to predict the future groundwater potential. The use of the recharge model for the future was on the assumption that the relationship between the recharge and the predictors in the past holds true in the future; however, given there was a wide range of climates for sites used to develop the model, this is likely to be one of the smaller uncertainties in the overall analysis. Additionally, Chapter 5 considered two future food scenarios which are highly uncertain given the current state of knowledge. Finally, it was assumed that there will be no future shifts in the ratio of surface water and groundwater usage.

### 6.5 Future Research Directions

This study has fulfilled all the stated objectives in Chapter 1 and has made unique contributions to enhance the knowledge on groundwater resources and groundwater irrigation. However, the limitations and assumption in this study discussed above (Section 6.4) open scope for further research.

Modelling any aspect of groundwater resources is inherently challenging due to the high heterogeneity in both vadose zone and aquifers. Human interaction with the water cycle adds further complexity. A study of this scale is made possible only by simplifying and ignoring
many processes involved. One such aspect that is excluded from this study is the return flow from irrigation. Inclusion of return flow in the analysis is a potential way of improving this research in future. One of the unanswered questions in this research is how the return flow will vary with improved irrigation efficiency? Here it was assumed that losses due to inefficiency can’t be recovered for future use. The dynamics between return flow and irrigation efficiency improvement will be an interesting aspect to explore as well. In addition, as data availability was one of the main factors limiting this research, a finer resolution data both temporally and spatially will help to get a more exact estimate of the issues demonstrated in this research. Currently all the analysis in this thesis were conducted at annual scale which failed to capture the intra annual variations in the stress during the cropping season. Finer spatial analysis would strengthen the insights from this study into the heterogeneity of the system.

Another research area of importance is the potential and feasibility of the improvement of irrigation efficiency and irrigation productivity improvement from a groundwater perspective. In this research, only the possibility of increasing the overall efficiency and productivity was evaluated, but the question on how to achieve these targets is unanswered. The ability to implement efficient irrigation systems will vary from country to country and even varies within the same country. A detailed study of various techniques to improve the efficiency and productivity at a regional to smaller scale will take the concept presented in this thesis to a more practical level. Another potential question that needs to be answered is ‘which of anthropogenic impact or climate change impact will be the predominant cause of changing stress on groundwater resources in the future?’. Identification of the predominant factor will help in formulating focused adaptation policies.

### 6.6 Conclusion

This research investigated the relationship between groundwater stress and dependent food production at a global scale by studying the current and future stress on global groundwater. The key conclusions derived from this work are as follows:
• Precipitation, potential evapotranspiration and land use are the most significant
predictors of groundwater diffuse recharge globally.

• Predictions from the recharge model developed in this research are comparable with
existing global groundwater recharge estimates.

• Irrigated food production is stressing the groundwater resources globally. One third
of the countries with groundwater irrigation are over exploiting their groundwater.

• Groundwater stress is highly focused in heavily populated areas. 80% of the global
non-renewable groundwater withdrawal occurs in six countries.

• 450 million tonnes of global annual food production are from non-renewable
groundwater exploitation. A tenth of the world population is fed with the food produced
by depleting groundwater resources.

• Increases in irrigation efficiency and irrigation productivity are a potential means of
reducing groundwater stress without compromising food security. It is estimated that
increasing irrigation efficiency and irrigation productivity can reduce global food
production from non-renewable groundwater extraction by three quarters.

• For constant crop area, global groundwater irrigation demand would increase by 7%
and 6% by 2080 in RCP 4.5 and 8.5 respectively. This is equivalent to an additional
11 million ML and 4 million ML of irrigation water required every year, respectively.

• Despite projected increases in recharge, climate change is likely to increase the stress
on groundwater resources. In the varying food demand scenario, by 2080, 25% (RCP
4.5) and 20% (RCP 8.5) of the total food will be produced by over exploiting the
groundwater which is equivalent to an additional 112 and 90 million tonnes of food production every year from overstressing groundwater in the respective RCPs.
Appendix

Table A1. Non-renewable groundwater abstraction (NGRA), associated unsustainable food production and the savings in all three stress remediation scenarios for selected major groundwater stressed countries.

<table>
<thead>
<tr>
<th>Area</th>
<th>Income group</th>
<th>Total production (tonnes)</th>
<th>Stress category</th>
<th>NRGA (10^6 ML/y)</th>
<th>Un Sustainable food production (10^6 tonnes)</th>
<th>Unsustainable food production as Scenario S2</th>
<th>Scenario S2a</th>
<th>Scenario S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>India</td>
<td>LMIC</td>
<td>2.5E+09</td>
<td>Overexploited</td>
<td>4.0E+07</td>
<td>1.7E+08</td>
<td>6.75</td>
<td>2.0E+07</td>
<td>8.3E+07</td>
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<tr>
<td>Pakistan</td>
<td>LMIC</td>
<td>5.8E+08</td>
<td>Overexploited</td>
<td>1.4E+07</td>
<td>5.7E+07</td>
<td>9.79</td>
<td>2.6E+07</td>
<td>1.0E+07</td>
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<tr>
<td>China</td>
<td>LMIC</td>
<td>2.8E+09</td>
<td>Heavily exploited</td>
<td>3.3E+06</td>
<td>3.4E+07</td>
<td>1.23</td>
<td>1.7E+06</td>
<td>1.8E+07</td>
</tr>
<tr>
<td>Iran</td>
<td>LMIC</td>
<td>4.0E+08</td>
<td>Overexploited</td>
<td>3.0E+06</td>
<td>1.4E+07</td>
<td>3.54</td>
<td>1.2E+06</td>
<td>5.6E+07</td>
</tr>
<tr>
<td>Turkey</td>
<td>LMIC</td>
<td>2.7E+08</td>
<td>Overexploited</td>
<td>8.8E+05</td>
<td>1.1E+07</td>
<td>3.92</td>
<td>5.6E+04</td>
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<td>6.1E+06</td>
<td>2.36</td>
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<tr>
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<td>HIC</td>
<td>2.4E+09</td>
<td>Heavily exploited</td>
<td>6.1E+05</td>
<td>6.0E+06</td>
<td>0.25</td>
<td>1.0E+06</td>
<td>9.9E+05</td>
</tr>
<tr>
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<td>1.4E+07</td>
<td>Overexploited</td>
<td>3.0E+04</td>
<td>5.4E+06</td>
<td>38.1</td>
<td>1.5E+04</td>
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<tr>
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<td>Type</td>
<td>Year</td>
<td>Status</td>
<td>Value 1</td>
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<td>Value 4</td>
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<td>Overexploited</td>
<td>1.2E+06</td>
<td>5.4E+06</td>
<td>2.03</td>
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<td>2.0E+05</td>
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LMIC: Low and middle income country  
HIC: High income country
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