ECONOMIC ALLOCATION OF WATER TO CROPS IN INTERNATIONAL CONTEXT

A NATIONAL AND GLOBAL PERSPECTIVE

Hatem Chouchane

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ECONOMIC ALLOCATION OF WATER TO CROPS IN INTERNATIONAL CONTEXT

A NATIONAL AND GLOBAL PERSPECTIVE

DISSERTATION

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the degree of doctor at the University of Twente,

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"It always seems impossible until it's done."

Nelson Mandela

Summary

Many countries are facing severe water scarcity, which is a huge handicap for food production. Understanding water allocation and the relationship between water availability and trade could help to see how trade worsens or mitigates water scarcity and how trade contributes to global water use efficiency. The goal of this thesis is to (i) investigate the economic efficiency of water and land allocation in crop production, (ii) identify possible pathways to improve crop allocation considering comparative advantage and (iii) explore the relationship between water scarcity and crop trade. The first sub goal is approached by taking Tunisia as a case study, the second sub goal is approached by a global study and the third sub goal is approached with both one national and one global study.

The water footprint of Tunisia from an economic perspective. The aim of this study is to quantify and analyse the water footprint within Tunisia at national and sub-national level, assessing green, blue and grey water footprints for the period 1996-2005. It also assesses economic water and land productivities related to crop production for irrigated and rain-fed agriculture, and water scarcity. Green, blue and grey WF estimates are mainly derived from a previous grid-based (5 × 5 arc minute) global study for the period 1996-2005. The green WF refers to consumption of rainwater, the blue water footprint to consumption of groundwater and surface water, and the grey WF to the volume of water required to assimilate pollutants (focusing here on nitrogen pollution). The study adds to earlier WF studies for Tunisia by putting emphasis on the analysis of the economic dimension of water use. The study finds that the water footprint of crop production gave the largest contribution (87%) to the total national water footprint. At national level, tomatoes and potatoes were the main crops with relatively high economic water productivity, while olives and barley were the main crops with relatively low productivity. In terms of economic land productivity, oranges had the highest productivity and barley the lowest. South Tunisia had the lowest economic water and land productivities. Economic land productivity was found to explain more of the current production patterns than economic water productivity, which may imply opportunities for water saving.

Virtual water trade patterns in relation to environmental and socio-economic factors: a case study for Tunisia. This study aims to analyse the dynamics in virtual water trade of Tunisia in relation to environmental and socio-economic factors such as gross domestic product (GDP), irrigated land, precipitation, population and water scarcity. The AquaCrop model of the Food and Agriculture Organization of the United

Nations was used to estimate the WF of crop production for six crops over the period 1981-2010. Net virtual water import (NVWI) is quantified at yearly basis. Regression models are used to investigate dynamics in NVWI in relation to the selected factors. It is found that: (a) NVWI during the study period for the selected crops is not influenced by blue water scarcity, (b) NVWI correlates in two alternative models to either population and precipitation (model I) or to GDP and irrigated area (model II), (c) the models are better in explaining NVWI of staple crops (wheat, barley, potatoes) than NVWI of cash crops (dates, olives, tomatoes), (d) using model I, we are able to explain both trends and inter-annual variability for rain-fed crops while model II performs better for irrigated crops and is able to explain trends significantly; no significant relation is found, however, with variables hypothesized to represent inter-annual variability.

Expected increase in staple crop imports in water-scarce countries in 2050. International food trade is mostly analysed in relation to food demand and preferences and differences in prices of land, labour and other inputs to food production, governmental subsidies and taxes and international trade agreements. Water scarcity as a driver of food trade can easily be overlooked because water prices and water scarcity are a negligible part of the prices of traded food commodities. In many countries, water scarcity is real though, even though not translated into a price. This chapter aims to study the relation between import of staple foods (including cereals, roots and tubers) and water scarcity with a long-term and global perspective. The net import of staple crops in kcal/y per capita is analysed in relation to water availability per capita for the period 1961-2010, considering five decadal averages. The relation found is used together with the low, medium and high population growth scenarios from the UN (United Nations, 2015) to project future staple crops import in water-scarce countries for the year 2050. Additionally, uncertainties related to the three population scenarios and related to the regression analysis were investigated. As a result of population growth in water-scarce countries alone, global international trade in staple crops is projected to increase by a factor of 1.4 to 1.8 towards 2050 (compared to the average in 2001-2010), in order to meet the staple food needs of the 42 most water-scarce countries in the world. Amongst others, this raises the question of where additional amounts of staple crops in the future could be sourced from, and what additional water and other environmental impacts that may have in these other countries.

Changing global cropping patterns to minimize blue water scarcity in the world's hotspots. Previous studies on water saving through international food trade focussed either on comparing water productivities among food-trading countries or on analysing food trade in relation to national water endowments. This study, consider, for the first time, both differences in water productivities and water endowments to analyse comparative advantages of countries for different types of crop production. A linear optimization algorithm is used to find modifications in global cropping patterns that reduce blue water scarcity in the world's hotspots, under the constraint of current global production per crop and current cropland areas. The optimization considers national water and land endowments as well as water and land productivity per country per crop. The results are used to assess national comparative advantages and disadvantages for different crops. When allowing a maximum expansion of harvested area per crop per country of 10%, the blue water scarcity in the world's most water-scarce countries can be greatly reduced. In this case, we could achieve a reduction of the current blue water footprint of crop production in the world of 9% and a decrease of global total harvested area of 4%.

Conclusion. This research has shown that global food trade is partly influenced by water scarcity patterns. Using information on differences in water productivities and water endowment to determine where to cultivate which crops could decrease global water scarcity. At national level, some policies are still focusing on self-efficiency which is holding some water-scarce countries from mitigating their water scarcity. A WF assessment could provide a better understanding of water use efficiency of blue water resources and thus improvements of national policies. The thesis contributes to the research field of water footprint assessment and virtual water trade studies in several ways. First, the work contributes by taking the economic perspective of water and land allocation together within a WF assessment, while earlier WF studies focus on water alone and stick to a physical, non-economic perspective. Second, it presents an examination of virtual water trade patterns in relation to the internal factors of a water-scarce country. Third, it gives the first-ever study that uses an empirical correlation between virtual water import and water scarcity to forecast likely future changes in international trade given population growth and associated water scarcity increase. Finally, for the first time, this work assesses the comparative advantage and disadvantage in a global study including all main crops and many countries whereas other comparative advantage studies are mostly limited to a few crops and a few countries.

Samenvatting

Veel landen hebben te maken met ernstige waterschaarste, wat enorm nadelig is voor voedselproductie. Het begrijpen van waterallocatie en de relatie tussen waterbeschikbaarheid en handel, zou kunnen helpen om te zien hoe handel de waterschaarste verergert of vermindert, en hoe handel bijdraagt aan de wereldwijde efficiëntie van watergebruik. Het doel van deze dissertatie is om (i) de economische efficiëntie van water- en landallocatie in de akkerbouw te onderzoeken, (ii) mogelijke routes te identificeren om de productielocaties van gewassen te verbeteren op basis van comparatieve voordelen en (iii) de relatie tussen waterschaarste en handel in gewassen te onderzoeken. Het eerste subdoel is benaderd door Tunesië als een case study te nemen, het tweede subdoel is benaderd door een globale studie en het derde subdoel is benaderd met zowel een nationaal als een wereldwijd onderzoek.

De watervoetafdruk van Tunesië vanuit een economisch perspectief. Het doel van deze studie is om de watervoetafdruk (WF) in Tunesië op nationaal en subnationaal niveau te kwantificeren en te analyseren voor de periode 1996-2005, en daarbij het onderscheid te maken tussen de groene, blauwe en grijze WF. Tevens worden de economische water- en landproductiviteiten met betrekking tot de productie van gewassen voor geïrrigeerde en regengevoede landbouw ingeschat, evenals waterschaarste. Groene, blauwe en grijze WF-schattingen zijn voornamelijk afgeleid van een eerdere, op een raster gebaseerde (5 × 5 boogminuten) wereldwijde studie voor de periode 1996-2005. De groene WF verwijst naar de consumptie van regenwater, de blauwe WF naar de consumptie van grond- en oppervlaktewater en de grijze WF naar het volume water dat nodig is om verontreinigende stoffen te assimileren (met betrekking tot stikstofverontreiniging). De studie maakt een stap ten opzichte van eerdere WF-studies voor Tunesië door de nadruk te leggen op de analyse van het economische aspect van watergebruik. Uit de studie blijkt dat de WF van gewasproductie de grootste bijdrage (87%) levert aan de totale nationale WF. Op nationaal niveau waren tomaten en aardappelen de voornaamste gewassen met een relatief hoge economische waterproductiviteit, terwijl olijven en gerst de voornaamste gewassen waren met een relatief lage productiviteit. In termen van economische landproductiviteit hadden sinaasappelen de hoogste productiviteit en gerst de laagste. Zuid-Tunesië had de laagste economische water- en landproductiviteiten. De economische landproductiviteit bleek meer van de huidige productiepatronen te verklaren dan de economische waterproductiviteit, wat kansen op waterbesparing kan inhouden.

Virtuele waterhandelspatronen in relatie tot milieu- en socio-economische factoren: een case study voor Tunesië. Deze studie heeft tot doel de dynamiek in de virtuele waterhandel van Tunesië te analyseren in relatie tot milieu- en socio-economische factoren zoals het bruto binnenlands product (BBP), geïrrigeerd akkerland, neerslag, bevolking en waterschaarste. Het AquaCrop-model van de Voedsel- en Landbouworganisatie van de Verenigde Naties is gebruikt om de WF van gewasproductie voor zes gewassen in de periode 1981-2010 te schatten. De netto virtuele waterimport (NVWI) wordt op jaarbasis gekwantificeerd. Regressiemodellen worden gebruikt om de dynamiek in NVWI te onderzoeken in relatie tot de geselecteerde factoren. Het blijkt dat: (a) NVWI tijdens de onderzoeksperiode voor de geselecteerde gewassen niet wordt beïnvloed door blauwe waterschaarste, (b) de NVWI correleert in twee alternatieve modellen met populatie en neerslag (model I) of met het BBP en geïrrigeerd gebied (model II), (c) de modellen zijn beter in het verklaren van NVWI van basisvoedselgewassen (tarwe, gerst, aardappelen) dan NVWI van handelsgewassen (dadels, olijven, tomaten), (d) met behulp van model I kunnen we zowel beide trends als de variaties over de jaren heen voor regengevoede gewassen verklaren, terwijl model II beter werkt voor geïrrigeerde gewassen en trends goed kan verklaren; er wordt echter geen significante relatie gevonden met variabelen waarvan werd verondersteld dat deze variaties over de jaren heen vertegenwoordigen.

Verwachte toename van import van basisvoedselgewassen in landen met waterschaarste in 2050. Internationale voedselhandel wordt meestal geanalyseerd in relatie tot voedselvraag en –voorkeuren, en verschillen in prijzen van land, arbeid en andere inputs voor voedselproductie, overheidssubsidies en -belastingen en internationale handelsovereenkomsten. Waterschaarste als drijvende kracht achter de handel in levensmiddelen kan gemakkelijk over het hoofd worden gezien, omdat waterprijzen en waterschaarste een verwaarloosbaar deel uitmaken van de prijzen van verhandelde voedselproducten. In veel landen is waterschaarste echter reëel, hoewel het niet in een prijs is vertaald. Dit hoofdstuk is bedoeld om de relatie tussen de import van basisgewassen (waaronder granen, wortelgewassen en knollen) en waterschaarste te bestuderen met een lange termijn en mondiaal perspectief. De netto import van basisgewassen in kcal per jaar per hoofd van de bevolking, wordt geanalyseerd in relatie tot de waterbeschikbaarheid per hoofd van de bevolking voor de periode 1961-2010, waarbij de gemiddelden van vijf decennia worden aangehouden. De gevonden relatie wordt gebruikt in combinatie met de lage, gemiddelde en hoge bevolkingsgroeiscenario's van de VN (Verenigde Naties, 2015) om de toekomstige import van basisgewassen in landen met waterschaarste voor het jaar 2050 te beramen. Daarnaast zijn de onzekerheden met betrekking tot de drie populatiescenario's en met betrekking tot de regressieanalyse onderzocht. Als gevolg van bevolkingsgroei in alleen waterschaarse landen, zal de mondiale internationale handel in basisgewassen naar verwachting met een factor van 1,4 tot 1,8 toenemen tot 2050 (vergeleken met het gemiddelde in 2001-2010) om te voorzien in de behoefte aan basisvoedsel van de 42 landen die de hoogste mate van waterschaarste ervaren ter wereld. Dit roept onder meer de vraag op waar in de toekomst mogelijk meer basisgewassen vandaan gehaald kunnen worden, en welke water-gerelateerde en andere milieueffecten dit aldaar zal hebben.

Wereldwijde voedselproductiepatronen veranderen om blauwe waterschaarste in 's werelds hotspots te minimaliseren. Voorgaande studies over waterbesparing door middel van internationale voedselhandel richtten zich ofwel op het vergelijken van waterproductiviteiten tussen voedselhandellanden of op het analyseren van voedselhandel in relatie tot nationale waterbeschikbaarheid. In deze studie worden voor het eerst zowel verschillen in waterproductiviteit als waterbeschikbaarheid meegenomen in de analyse van de comparatieve voordelen van landen voor de productie van verschillende soorten gewassen. Een lineair optimalisatiealgoritme wordt gebruikt om wijzigingen te vinden in mondiale voedselproductiepatronen die blauwe waterschaarste verminderen in 's werelds hotspots, onder de randvoorwaarden van de huidige wereldwijde productie per gewas en de huidige akkerlandgebieden. De optimalisatie houdt rekening met nationale water- en landbeschikbaarheid en met water- en landproductiviteit per land per gewas. De resultaten worden gebruikt om nationale comparatieve voor- en nadelen voor verschillende gewassen te beoordelen. Wanneer een maximale uitbreiding van het geoogste gebied per gewas per land van 10% wordt toegestaan, kan de blauwe waterschaarste in de landen waar deze schaarste het grootste is ter wereld sterk worden verminderd. In dit geval zouden we een vermindering van de huidige blauwe watervoetafdruk van mondiale akkerbouw van 9% en een afname van het totale geoogste areaal van 4% kunnen realiseren.

Conclusie. Dit onderzoek heeft aangetoond dat de mondiale voedselhandel deels wordt beïnvloed door waterschaarstepatronen. Het gebruik van informatie over verschillen in waterproductiviteit en waterbeschikbaarheid om te bepalen waar welke gewassen het beste verbouwd kunnen worden, kan wereldwijde waterschaarste verminderen. Op nationaal niveau zijn sommige beleidsmaatregelen nog steeds gericht op self-efficiency, die sommige landen met waterschaarste ervan weerhoudt hun waterschaarste te verminderen. Een WF-analyse kan een beter inzicht geven in de efficiëntie van het gebruik van blauwe waterreserves en daarmee leiden tot verbetering van nationaal beleid. De dissertatie draagt op verschillende manieren bij aan het onderzoeksveld van watervoetafdrukanalyse en virtuele waterhandel. Ten eerste draagt het werk bij door het economische perspectief van water- en landallocatie samen te nemen binnen een WF-analyse, terwijl voorgaande WF-onderzoeken zich alleen richten op water en vasthouden aan een fysiek, niet-economisch perspectief. Ten tweede presenteert het een onderzoek naar virtuele waterhandelspatronen in relatie tot de interne factoren van een land met waterschaarste. Ten derde brengt het de allereerste studie voort die een empirische correlatie gebruikt tussen virtuele waterimport en waterschaarste om waarschijnlijke toekomstige veranderingen in de internationale handel te voorspellen, gezien de bevolkingsgroei en de daarmee samenhangende toename in waterschaarste. Tot slot evalueert dit werk voor het eerst het comparatieve voordeel en nadeel in een wereldwijd onderzoek met inbegrip van alle belangrijke gewassen en veel landen, terwijl andere studies over comparatieve voordelen veelal beperkt zijn tot slechts een paar gewassen en een paar landen.

1. Introduction

1.1. Research background

Freshwater is not only essential for life functions but also to produce our food, clothes and energy. Freshwater is a renewable but finite resource (Hoekstra 2013); hence, for the eighth year in a row water crisis has been recognized by the World Economic Forum as one of the top risks that the global economy is facing in terms of potential impact (WEF 2019). Already two-thirds of the world population are living under severe water scarcity at least one month of the year (Mekonnen and Hoekstra 2016). Agriculture is both a cause and a victim of water scarcity (FAO 2016). Agriculture is by far the largest consumer of freshwater, accounting for 92% of total water consumption globally (Hoekstra and Mekonnen 2012). Societal and climate changes are estimated to further exacerbate water scarcity and reduce the potential of sufficient food production in many countries (Godfray et al. 2010, Thornton et al. 2018). This raises the importance of improving the efficiency of water allocation in crop production, considering spatial differences in water scarcity and increased future food demands.

Water scarcity indicators have evolved during the past few decades. Falkenmark (1989) defined the water stress indicator as the annual availability of surface water and groundwater flow per capita in a country, considering a country to be severely stressed if per capita water availability drops below 500 m^3/y, while a country is not considered to be stressed if the per capita water availability exceeds 1700 m^3/y. The indicator is a bit simplistic by ignoring the temporal distribution of water demand and availability within the year and ignoring the possibility to import food. Another widely used indicator is the water withdrawal to availability ratio (e.g. Oki and Kanae (2006), Vörösmarty et al. (2000)), which considers a country to be severely water-stressed if the ratio of blue water withdrawal to renewable blue water resources exceeds 40%. This again is an indicator defined on annual basis, but unlike the Falkenmark it does consider actual water use in a country rather than the theoretical requirement given population size. More recently, Hoekstra et al. (2012) define blue water scarcity as the ratio of blue water footprint (WF) in a country or a river basin to the blue water availability of that country or basin. They apply this indicator on a monthly basis. By considering the blue water footprint, it is the consumptive use of water, rather than the gross abstraction of water, this indicator provides a more accurate measure of water scarcity since a ignificant share of withdrawn water returns to rivers and aquifers and becomes available for reuse.

Next to the traditional measure of blue water withdrawal, the WF is a comprehensive indicator of consumptive and degradative water use (Hoekstra et al. 2011). The WF looks at the direct and indirect water use from either a consumer or producer point of view (Hoekstra 2017). Water Footprint Assessment refers to a variety of methods to quantify and map the WF of specific processes, products, producers or consumers, to assess the environmental, social and economic sustainability of WFs at catchment or river basin level and to assess the effectiveness of measures to reduce WFs (Hoekstra 2017). The WF of a product is the volume of freshwater consumed or polluted to produce the product, expressed in terms of water volume per unit of product (usually m^3/t), measured over the full supply chain. The WF has three components: blue, green and grey. The blue WF refers to consumption (net abstraction) of blue water resources (surface water and groundwater); the green WF refers to consumption of green water resources (rainwater stored in the soil); and the grey WF indicates water pollution and is defined as the volume of freshwater that is required to assimilate a load of pollutants, given natural background concentrations and existing ambient water quality standards (Hoekstra et al. 2011). The green and blue WF together are sometimes called the consumptive WF, while the grey WF is the degradative WF.

Closely related to the consumptive WF per unit of product is water productivity (WP), which is the reverse. WP in crop production is generally defined as the ratio of agricultural output to the amount of water consumed. Improving WP in order to increase water use efficiency and mitigate water scarcity has been extensively investigated (Bouman 2007, Chukalla et al. 2015, Fan et al. 2012, Molden et al. 2010, Nouri et al. 2019, Sadler et al. 2005). However, expressing WP in physical term hides the economic benefits from water use, therefore it is useful to consider economic water productivity (EWP), defined as the economic output per unit of water consumed (Pereira et al. 2009). There is a great scope for increasing EWP by increasing the value generated by water use. While there are good ecological and societal reasons to increase WP, particularly in water-stressed regions, farmers generally manage labour and other inputs to maximize their economic gains. Increasing WP is typically not their main focus (Molden et al. 2010). Mostly national agricultural strategies focus on options to reduce water demand and increase supply, but they ignore to evaluate how efficient water is allocated based on physical and economic WP (Schyns and Hoekstra 2014). By linking water usage to economic return, EWP is a powerful measure of water use efficiency, which allows comparison between water allocation to alternative crops within the same country and between countries.

Besides saving water through increasing WP, water-scarce countries are increasingly filling the gap between local supply and demand by importing water-intensive products from outside (Abdelkader et al. 2018, Antonelli and Sartori 2015). In this way, countries are importing ‘virtual’ water that is embedded in imported products (Allan 1998). Assessing virtual water embedded in traded products and investigating water saving per countries through their engagement in virtual water trade has been the objective of several studies (Chapagain et al. 2006, Hoekstra and Hung 2005, Konar et al. 2013, Zhang et al. 2016). Less attention has been given to understanding the relationship between trade and socio-economic factors and especially between virtual water trade of a country and its water scarcity and availability. International trade in grains has a significant role in achieving food security and in compensating local water deficits (Yang and Zehnder 2002). However, water availability is not found to have a significant relationship with international food trade (Kumar and Singh 2005, Ramirez-Vallejo and Rogers 2004, Verma et al. 2009); it is rather GDP per capita that is found to have a high significance in explaining the variations in food imports (Tamea et al. 2014, Yang et al. 2003). Han et al. (2018) studied the global supply chain of water use distinguishing between production- and consumption-based water flows. They found a substantial proportion of the embodied international water transfer to be inefficient and imbalanced, with a significant share of embodied water transferred from regions with lower water resource per capita to the higher ones. In a recent study, using a partial least squares structural equation model, Sun et al. (2019) evaluated the impact of regional social-economic patterns on virtual water flows related to grain trade. They found a significant causal relation between national economic parameters like GDP, population, urbanization and the Engel’s coefficient, and (international?) virtual water flows related to grain trade. Virtual water flows between regions change the original spatial distribution pattern of water resources, which has a significant impact on the water resources in the water import and export regions; virtual water flows increase the pressure of water resources in grain export areas (Sun et al. 2019).

According to international trade theory (dating back to Ricardo (1821)), countries can profit from trade by focussing on the production and export of goods for which they have a comparative advantage while importing other goods in which they have a comparative disadvantage. Following the Ricardian model, a country can best focus on producing the goods and services for which they have relatively high productivity, while according to the Heckscher-Ohlin (H-O) theory (Heckscher 1919, Ohlin 1933), a country can best specialize in producing and exporting products that use production factors that are most abundant (Hoekstra 2013). Optimally, a country well-endowed in water, land or labour will intend to produce and export water intensive, land-intensive or labour-intensive products respectively. However, this is not always the case. When testing the H-O theory, Leontief (1954) found that the US, which is well-endowed in capital relative to labour, is importing capital-intensive goods while exporting labour-intensive good, which is counter-intuitive to the H-O theorem. This is known as the Leontief-paradox. In the field of water, it was found that water-scarce north China is producing and exporting water-intensive products while water-abundant south China imports water-intensive goods (Guan and Hubacek 2007, Ma et al. 2006). In a recent study, based on the spatial distribution of resources productivity and opportunity cost of water, land and labour, Zhao et al. (2019) assessed the regional comparative advantage of agricultural and non-agricultural sectors across Chinese provinces. They found that virtual water flows are mainly based on differences in comparative advantage of land productivity. Most of the previous studies on water saving through trade either focussed on comparing water productivities among food trading countries (Chapagain et al. 2006, Yang et al. 2006), or on analysing food trade in relation to water endowments (Yang et al. 2003). In this thesis, we will consider, for the first time, how both differences in productivities and endowments of water and land can be taken to analyse the comparative advantages of countries for different types of crop production.

1.2. Research objective and questions

The objective of this research is to investigate the economic efficiency of water and land allocation in crop production, the possible pathways to improve crop allocation considering comparative advantage and to explore the relationship between water scarcity and crop trade. For that, the following research questions are formulated:

Q1. How are water and land allocated in crop production from an economic perspective?

Q2. What are the main socio-economic driving forces of crop trade?

Q3. How does water scarcity affect international crop trade?

Q4. How can land and water resources be better allocated in a way to reduce water scarcity?

The first two questions will be addressed from a national perspective, taking Tunisia as a case, while for the last two questions I will take a global perspective.

1.3. Research approach and thesis outline

This thesis consists of two parts: the first part considers Tunisia, an arid to semi-arid country in North Africa that faces substantial problems of water scarcity (Chapters 2 and 3), while the second part considers the world as a whole, considering international trade in relation of the water endowments and productivities of different countries (Chapters 4 and 5) (Figure1.1).

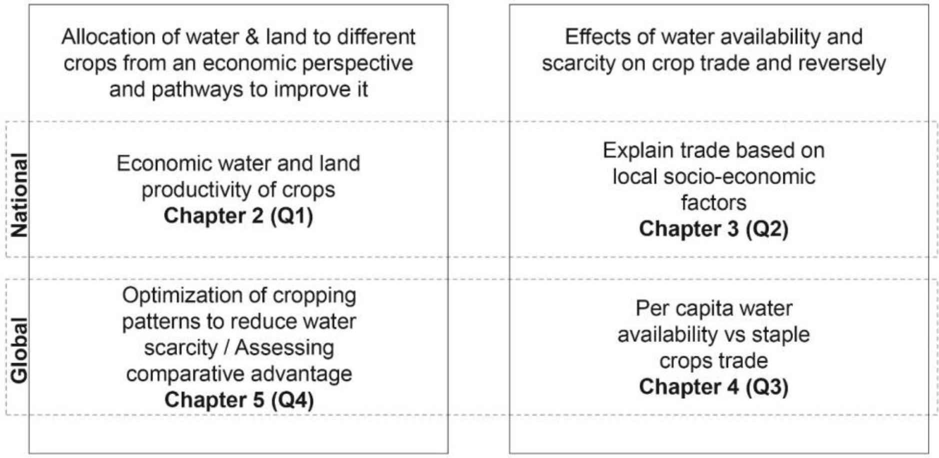

Figure 1.1. Structure of the thesis

Chapter 2 quantifies and analyses the water footprint within Tunisia at national and sub-national level, assessing green, blue and grey water footprints for the period 1996-2005. It also assesses economic water and land productivities related to crop production for irrigated and rain-fed agriculture, and water scarcity (Question 1).

Chapter 3 empirically investigates the dynamics of virtual water trade of Tunisia in relation to environmental and socio-economic factors such as GDP, irrigated land, precipitation, population and blue water scarcity. It expands on traditional statistical analyses that try to explain trade volumes by investigating the extent to which water scarcity contributes to explaining virtual water flows embodied in trade flows. The water footprint of crop production is estimated using FAO's AquaCrop model for six crops over the period 1981-2010. Net virtual water import is quantified on yearly basis (Question 2).

Chapter 4 expands from the case study of Chapter 3 and explores, for the 42 most water-scarce countries in the world, the relationship between the net import of staple crops (including cereals, roots, and tubers) and per capita water availability for the period 1961-2010, considering five decadal averages. The relation found is used, together with the population growth scenarios from the United Nations, to project staple crop imports in water-scarce countries for the year 2050. The sensitivity of the outcomes to uncertainties are estimated by considering uncertainties related to future population projections and to the regression analysis. (Question 3)

Chapter 5 explores how the global cropping pattern can be changed in order to reduce blue water scarcity in the world's hotspots, considering water and land availability and productivity per country. This is done by using a linear programming optimization algorithm; the optimization objective is to minimize the maximum water scarcity under a number of constraints. First, per country, both rainfed and irrigated harvested area should not exceed the average total harvested area during the period 1996-2005. Second, the current allocated harvested area per country per crop can expand to a maximum fixed factor α (which is varied). Third, global production of each crop in the current situation must remain the same (Question 4).

2. The footprint of Tunisian from an economic perspective[1]

Abstract

This paper quantifies and analyses the water footprint of Tunisia at national and sub-national level, assessing green, blue and grey water footprints for the period 1996-2005. It also assesses economic water and land productivities related to crop production for irrigated and rain-fed agriculture, and water scarcity. The water footprint of crop production gave the largest contribution (87%) to the total national water footprint. At national level, tomatoes and potatoes were the main crops with relatively high economic water productivity, while olives and barley were the main crops with relatively low productivity. In terms of economic land productivity, oranges had the highest productivity and barley the lowest. South Tunisia had the lowest economic water and land productivities. Economic land productivity was found to explain more of the current production patterns than economic water productivity, which may imply opportunities for water saving.

The total blue water footprint of crop production represented 31% of the total renewable blue water resources, which means that Tunisia as a whole experienced significant water scarcity. The blue water footprint on groundwater represented 62% of the total renewable groundwater resources, which means that the country faced severe water scarcity related to groundwater.

2.1. Introduction

As one of the most arid countries in the Mediterranean, Tunisia suffers from high water scarcity. The shortage of water resources is a limiting factor to food production. Generally, water resources use is reported per economic sector, without explicitly indicating the precise purpose of water use. For instance, in the agricultural sector, the largest water-using sector in Tunisia, it is unusual to look at specific water use per type of crop. It is important to do so, however, in order to be able to assess the economic productivity of water use. In this paper, we apply the water footprint concept to address the issue of economic water productivity.

The water footprint (WF), introduced by Hoekstra (2003) as a comprehensive indicator of freshwater use, quantifies and maps water consumption and pollution in relation to

[1] This chapter has been published as:
Chouchane, H., Hoekstra, A.Y., Krol, M.S. and Mekonnen, M.M. (2015) The water footprint of Tunisia from an economic perspective. Ecological Indicators 52, 311-319.

production or consumption. The WF has three components: blue, green and grey (Hoekstra et al., 2011). The blue WF refers to consumption of blue water resources (surface and groundwater). The green WF refers to consumption of green water resources (rainwater). The grey WF measures water pollution and is defined as the volume of fresh water that is required to assimilate the load of pollutants given natural background concentrations and existing ambient water quality standards. The WF of a crop is generally expressed in terms of m^3/t or litre/kg but can also be expressed in terms of m^3 per monetary unit (Hoekstra et al., 2011). Garrido et al. (2009) show the usefulness of doing so in a case study for Spain. Mekonnen and Hoekstra (2014) show this for the case of Kenya, and Schyns and Hoekstra (2014) for the case of Morocco. Garrido et al. (2009) show that water scarcity affects water productivity; users become more efficient in their blue water use as water becomes scarcer, but this behavioural adaptation only occurs in regions where water is scarce and where blue water is the main contribution to total crop water use.

A concept closely related to WF is water productivity (WP). The increasing scarcity of fresh water and the important role that water plays in food production impose the need to optimise water use in all human activities, particularly in agriculture, the main water-using sector worldwide. There is no common definition of the term WP (Rodrigues and Pereira, 2009), but in all definitions WP refers to the ratio of the net benefits from crop, forestry, fishery, livestock or mixed agriculture systems to the amount of water used to produce those benefits. Physical WP can be defined as the ratio of agricultural output to the amount of water consumed ('crop per drop'), which is mostly expressed in either blue water withdrawal or total (green plus blue) water consumption through evapotranspiration (Kijne et al., 2003; Zwart and Bastiaanssen, 2004, 2007; Playan and Matoes, 2006; Molden, 2007). When water use is measured as green plus blue water consumption, physical WP (in t/m^3) is thus an inverse of the green plus blue WF (in m^3/t).

Expressing WP in physical terms does not give insight in the economic benefit of water use; therefore, it is useful to consider economic water productivity (EWP) as well (Cook et al., 2006; Pereira et al., 2009). EWP is defined as the value derived per unit of water used, i.e. 'dollar per drop' (Igbadun et al., 2006; Palanisami et al., 2006; Teixeira et al., 2008; Vazifedoust et al., 2008; Garrido et al., 2009). The scope for increasing the value per unit of water used in agriculture is often bigger than the scope for increasing physical WP (Molden et al., 2010).

In this paper we quantify and analyse the green, blue and grey WF within Tunisia, analyse the blue WF in the context of blue water availability and assess economic water and land productivities related to crop production for irrigated and rain-fed agriculture. The period of analysis is 1996-2005. The study adds to earlier WF studies for Tunisia (Chapagain and Hoekstra, 2004; Chahed et al., 2008; Chahed et al., 2011; Mekonnen and Hoekstra, 2011a; Hoekstra and Mekonnen, 2012) by putting emphasis on the analysis of the economic dimension of water use. The study focuses on the WF of production within Tunisia, rather than the WF of Tunisian consumption. The latter is partly located outside Tunisia. The external WF of Tunisian consumption is about 32% of the total WF of national consumption (Mekonnen and Hoekstra, 2011a); the current paper does not address this external WF. Furthermore, the study focuses on the WF of the crop sector, because this sector accounts for 87% of the total WF of production in the country (Mekonnen and Hoekstra, 2011a).

2.2. Method and Data

The study follows the terminology and methodology as set out in The Water Footprint Assessment Manual (Hoekstra et al., 2011), which contains the global standard for Water Footprint Assessment (WFA). We will put the blue WF of Tunisian production in the context of renewable blue water resources in order to assess water scarcity. Vörösmarty et al. (2000), Alcamo and Henrichs (2002), and Oki and Kanae (2006) consider a country to be severely water stressed if the ratio of blue water withdrawal to renewable blue water resources (runoff) is higher than 40%. Here, we define water scarcity based on blue water consumption (blue WF) rather than blue water withdrawal, which is more meaningful, because a significant share of withdrawn water returns to rivers and aquifers and becomes available for reuse (Hoekstra et al., 2012). We thus compare the blue WF to renewable blue water resources. Table 2-1 shows the water scarcity thresholds used in this study, equivalent to the thresholds used by Hoekstra et al. (2012). We calculate overall water scarcity on annual basis as the ratio of total blue WF to total renewable blue water resources, and groundwater scarcity as the ratio of the blue WF from groundwater sources to renewable groundwater resources.

In calculating water productivities, we distinguish between rain-fed and irrigated agriculture. Rain-fed agriculture only consumes rainwater, so that we can speak of green WP. In the case of irrigated agriculture, we distinguish between green and blue WP, because both rainwater and irrigation water are consumed. In irrigated agriculture, green

WP is defined as the yield that would be obtained based on rain only (assuming no irrigation) divided by the volume of green water consumed. Blue WP is defined as the additional yield obtained through irrigation divided by the volume of blue water (irrigation water) consumed (Hoekstra, 2013).

Table 2-1. Water scarcity thresholds.

Blue water scarcity levels *	**Water scarcity thresholds**
Low blue water scarcity	< 20%
Moderate blue water scarcity	20-30%
Significant blue water scarcity	30-40%
Severe water scarcity	> 40%

* Water scarcity is defined as blue water footprint / renewable blue water resources.

The yield obtained from rain only is estimated based on the equation proposed by Doorenbos and Kassam (1979):

$$\left(1-\frac{Y_a}{Y_m}\right) = K_y\left(1-\frac{ET_a}{CWR}\right) \qquad \text{(Eq. 2-1)}$$

where K_y is a yield response factor (water stress coefficient), Y_a the actual yield (kg/ha), Y_m the maximum yield, obtained under optimal water supply conditions (kg/ha), ET_a the actual crop evapotranspiration (mm/period) and CWR the crop water requirement (mm/period). Following this equation, the green-water based yield ($Y_{green,\ irrig}$) in irrigated agriculture can be calculated from:

$$\left(1-\frac{Y_{green,irrig}}{Y_{tot,irrig}}\right) = K_y\left(1-\frac{ET_{green}}{ET_{green}+ET_{blue}}\right) \qquad \text{(Eq. 2-2)}$$

Whereby $Y_{tot,irrig}$ is the yield occurring under full irrigation (rain + irrigation water), which equals the maximum yield Y_m; ET_{green} is the evapotranspiration of green water that would have occurred without irrigation; ET_{blue} is the evapotranspiration of blue water. Data on $Y_{tot,irrig}$, ET_{green}, ET_{blue} and K_y are obtained for all irrigated crop areas from the grid-based study of Mekonnen and Hoekstra (2010). The additional yield through irrigation is calculated as the total yield in irrigated agriculture ($Y_{tot,irrig}$) minus the yield that would be obtained without irrigation ($Y_{green,irrig}$).

Figure 2-1 shows the relation between yield and evapotranspiration during the growing period and visualizes green and blue WP through two subsequent slopes. The first (green) slope represents the green WP, while the second (blue) slope represents the blue WP.

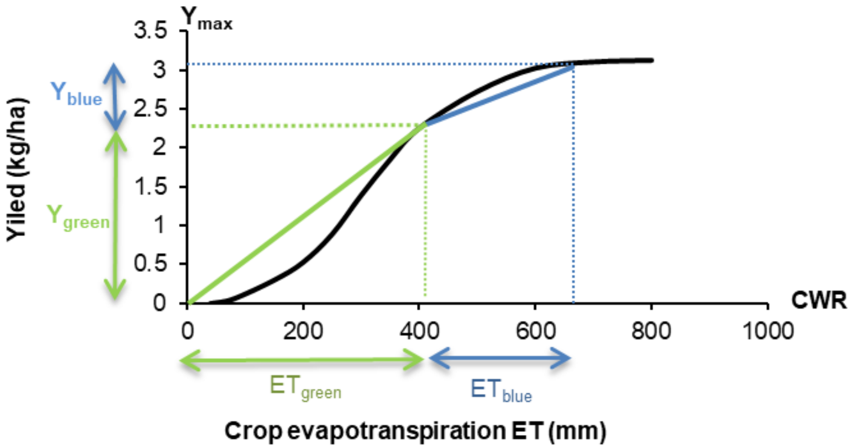

Figure 2-1. The relation between yield and evapotranspiration from a crop field. Green and blue water productivity appear as the slopes of each of the two-line segments drawn in the graph.

Table 2-2. Overview of input variables and data sources used.

Input variable	Source
Water footprint of crop production	Mekonnen and Hoekstra (2010, 2011b)
Water footprint in other sectors	Mekonnen and Hoekstra (2011a)
Yields and evapotranspiration in rain-fed and irrigated systems	Mekonnen and Hoekstra (2010)
Water resources availability and water withdrawal at national level	Ministry of Environment (2009)
Surface water availability and withdrawal at regional level	Ministry of Agriculture (2005a)
Groundwater availability and withdrawal at regional level	Ministry of Agriculture (2005b)
Crop values (producer prices)	FAOSTAT (FAO, 2009)

Economic water productivities (US$/m^3) are calculated by multiplying physical water productivities (kg/m^3) by crop value (US$/kg). Similarly, economic land productivities (US$/ha) are calculated by multiplying yields by crop value. For a farmer, blue EWP may be a relevant variable for production decisions, as blue water use goes along with direct production costs or blue water availability may be limiting production. Land productivity may influence decisions on crop choices if land availability is the most limiting factor for a farmer.

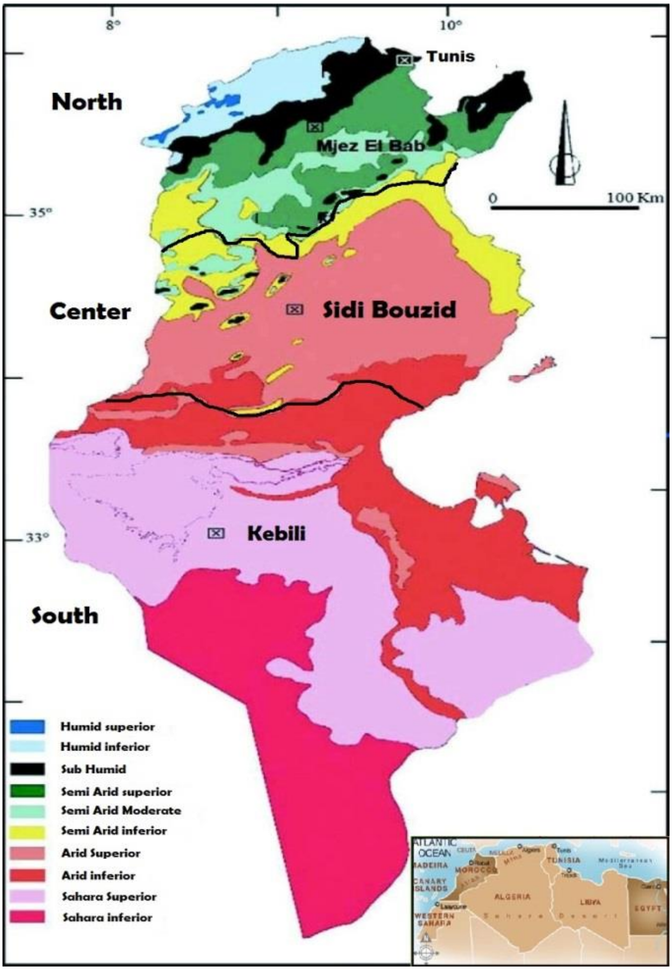

Figure 2-2 Bioclimatic map of Tunisia. Source: Chelbi et al. (2009).

The study is based on data for the period 1996-2005. Table 2-2 gives an overview of all input variables and data sources used in this study. We divided the country into three regions based on climate: North, Central and South (Figure 2-2). North has a

Mediterranean climate, South has a Sahara climate, while Central has a climate in between. Each region consists of governorates, administrative sub-units.

2.3. Results

2.3.1. Water Footprint of national Production

The total water footprint (WF) of Tunisian production was about 19 billion m^3 (billion m^3) per year (89% green, 8% blue, 3% grey) over the period 1996-2005. The WF of crop production gave the largest contribution to the total WF of production (87%), followed by grazing (11%). The remaining part (2%) represented domestic water supply, livestock production and industrial activities (Mekonnen and Hoekstra, 2011a).

Table 2-3. The average green, blue and grey water footprint of main crops and total water footprint of crop production in Tunisia (1996-2005).

Crop	Total water footprint (10^6 m^3/y)				Water footprint per tonne of crop (m^3/t)				Global average water footprint (m^3/t)			
	Green	**Blue**	**Grey**	**Total**	**Green**	**Blue**	**Grey**	**Total**	**Green**	**Blue**	**Grey**	**Total**
Almonds	790	90	50	930	17760	1950	1110	20820	4630	1910	1510	8050
Barley	1220	30	60	1310	3560	80	180	3820	1210	80	130	1420
Carrots	10	30	2	40	260	530	30	820	110	30	60	200
Dates	110	350	10	470	1030	3270	80	4390	930	1250	100	2280
Figs	70	40	4	120	2810	1740	170	4720	1500	1540	280	3280
Grapes	70	130	10	200	550	1080	60	1690	430	100	90	610
Olives	7270	270	30	7570	8790	330	40	9150	2470	500	50	3010
Oranges	40	20	2	70	370	230	20	620	400	110	50	560
Potatoes	40	40	10	80	110	120	20	260	190	30	60	290
Tomatoes	50	40	10	100	60	50	10	120	110	60	40	210
Wheat	3170	100	150	3420	2380	70	110	2560	1280	340	210	1830
Other crops	1980	190	112	2290								
Total	**14820**	**1330**	**450**	**16600**								

Source: Mekonnen and Hoekstra (2011a). Note that t /tonne refers to metric tonne.

The WFs of the main crops are listed in Table 2-3. The listed crops represent 86% of the total blue WF of crop production. Among these crops, almonds had the largest WF per unit of weight, about 20820 m^3/t, which is more than twice the global average WF for almonds. Tunisian almonds used about four times more green water than the global average, while they consumed about the global average amount of blue water. Tomatoes had the smallest WF of 120 m^3/t, which is below the global average (210 m^3/t). Dates, almonds, figs and grapes were the biggest blue water users with 3270, 1950, 1740 and

1080 m³/t respectively. These figures are higher than the global averages, especially for grapes, which used ten times the global average amount of blue water.

Olives alone accounted for about 46% of the total WF of crop production in Tunisia. About 79% of the total green WF was due to the production of olives (7.3 billion m³/y), wheat (3.2 billion m³/y) and barley (1.2 billion m³/y). The total blue WF was dominated by dates and olives (together 47%) and, to a lesser extent by grapes, wheat and almonds.

2.3.2. Water footprint of crop production at sub-national level

The total WF of crop production in Tunisia was about 16.6 billion m³/y (89% green, 8% blue, 3% grey). North Tunisia took the biggest share in the total WF of crop production (70%), followed by Central (26%) and South (4%) (Table 2-4; Figure 2-3). Regarding blue water, North Tunisia had the biggest share in the total blue WF, with 0.65 billion m³/y, which represents 49% of the total blue WF of crop production in the country. South and Central Tunisia followed with 28% and 23% respectively. In South Tunisia, the driest part of the country, the total WF of crop production was dominated by blue water (with a contribution of 68%).

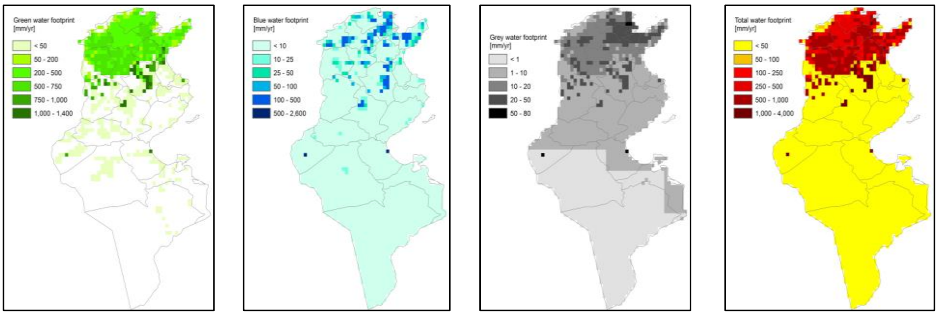

Figure 2-3 The green, blue, grey and total water footprint of crop production in Tunisia.

Table 2-4 shows the WF per unit of weight for the most important crops, for each of the three regions. The difference in WFs and crop water requirements in North and Central is not so big, but the values in South differ considerably, especially for olives, wheat, almonds, figs and barley. In terms of the blue WF, a unit of wheat or barley grown in South Tunisia used almost twelve times more blue water than the same crop grown in North, largely because irrigation is the dominant production system in South, whereas rain-fed production is dominant in Central and North. Almond and figs grown in Central Tunisia used less blue water than in the other regions, while tomatoes and carrots grown in South Tunisia had the smallest blue WF per tonne.

Table 2-4. The average green, blue and grey water footprint and crop water requirement of main crops in Tunisia per region (1996-2005).

	Crop	Water footprint per tonne of crop (m³/t)				Total water footprint (10⁶ m³/y)				Crop water requirement (m³/ha)
		Green	Blue	Grey	Total	Green	Blue	Grey	Total	
North	Almonds	16590	2480	1010	20090	380	60	20	460	9220
	Barley	3520	90	180	3790	930	10	50	990	4570
	Carrots	290	500	40	820	10	20	1	30	6340
	Dates	-	-	-	-	-	-	-	-	-
	Figs	2840	1680	170	4690	60	40	4	110	7780
	Grapes	780	1120	70	1970	30	40	3	70	7160
	Olives	8650	400	40	9080	4660	170	20	4850	8150
	Oranges	370	220	20	610	40	20	2	60	7780
	Potatoes	130	110	20	260	30	40	10	70	3550
	Tomatoes	70	40	10	120	40	30	10	70	3510
	Wheat	2360	90	110	2550	2820	70	130	3020	4980
	Other crops					1650	150	90	1910	
	Total					**10650**	**650**	**340**	**11640**	
Center	Almonds	18290	1490	1200	20980	410	30	30	470	9550
	Barley	3470	240	200	3910	290	10	20	320	4710
	Carrots	490	380	70	940	3	7	0	10	6650
	Dates	-	-	-	-	-	-	-	-	-
	Figs	3460	1200	220	4880	10	10	1	10	8030
	Grapes	700	1300	70	2060	30	50	3	90	7510
	Olives	8840	470	40	9350	2580	100	10	2690	8420
	Oranges	370	240	20	630	3	3	0	10	8020
	Potatoes	110	130	20	270	10	20	0	40	3660
	Tomatoes	80	40	10	120	10	10	2	20	3640
	Wheat	2350	230	120	2710	350	20	20	390	5120
	Other crops					300	30	10	340	
	Total					**4000**	**290**	**100**	**4390**	

Table 2-4. (continued) The average green, blue and grey water footprint and crop water requirement of main crops in Tunisia per region (1996-2005).
Source: Mekonnen and Hoekstra (2011b).

	Crop	Water footprint per tonne of crop (m^3/t)				Total water footprint (10^6 m^3/y)				Crop water requirement
		Green	Blue	Grey	Total	Green	Blue	Grey	Total	(m^3/ha)
South	Almonds	20810	2330	2080	25220	10	1	1	10	11780
	Barley	3770	1050	310	5130	2	1	0	3	6070
	Carrots	670	30	150	860	0	0	0	0	7760
	Dates	1040	3290	80	4390	110	350	10	470	13350
	Figs	4940	820	500	6260	0	0	0	0	9920
	Grapes	450	1870	70	2380	10	30	1	40	8730
	Olives	10750	930	80	11760	30	3	0	40	10390
	Oranges	210	510	30	750	0	0	0	0	9480
	Potatoes	70	210	30	310	0	0	0	0	4310
	Tomatoes	150	1	20	170	0	0	0	0	4500
	Wheat	2780	1230	210	4220	3	1	0	4	6610
	Other crops					0	4	0	4	
	Total					**160**	**390**	**10**	**560**	

2.3.3. Blue water footprint of crop production in the context of blue water availability

Tunisia has limited blue water resources, estimated at 4.87 billion m^3/y in 2005, of which 4.26 billion m^3/y are renewable (Ministry of Environment, 2009). The remaining part, 0.61 billion m^3/y, is fossil groundwater situated in South Tunisia, and expected to be exhausted in about 50 years at the current extraction rate (FAO, 2003).

The total renewable surface water (TRSW) was estimated at 2.70 billion m^3/y (Table 2-5). This amount represents the average calculated over a 50-year period. Surface water contributions come from four distinct natural regions. The far northern part of North Tunisia, with only 3% of the total Tunisian land area, has on average about 0.96 billion m^3/y of TRSW, which is about 36% of the national total. The basins of Majerda and Melian in North Tunisia provide an average of 1.23 billion m^3/y (45% of the national total). Central Tunisia, including the watersheds Nebhana, Marguellil, Zeroud and Sahel, has an average TRSW of 0.32 billion m^3/y (12%). South Tunisia, which represents about 62% of the total national land area, has very irregularly available surface water resources, averaging 0.19 billion m^3/y, or 7% of the national TRSW (Ministry of Environment, 2009).

The total groundwater resources are estimated at 2.17 billion m^3/y in 2005 (Ministry of Environment, 2009), of which 0.75 billion m^3/y are from shallow aquifers (depth less than 50 m) and 1.42 billion m^3/y from deep aquifers (deeper than 50 m) of which 0.61 billion m^3/y are non-renewable. The total renewable groundwater is thus 1.56 billion m^3/y. North Tunisia has 50% of the shallow aquifer resources; Central Tunisia contains 33%, while South contains 17%. Regarding deep aquifers, South has the biggest share (55%), followed by Central (23%) and North (22%).

Table 2-5. Blue water footprint of crop production in the context of blue water availability.

	Blue water footprint (10^6 m^3/y)			Blue water resources (10^6 m^3/y)					Water scarcity (%) [e]	
				Renewable blue water resources			Fossil [d]	Total		
	Ground water [a]	Surface water [a]	Total [b]	Ground water [d]	Surface water [c]	Total			Ground water	Overall
North	320	330	650	680	2190	2870		2870	47	23
Central	270	20	290	570	320	890		890	47	32
South	380	10	390	310	190	500	610	1110	123	78
Total	970	360	1330	1560	2700	4260	610	4870	62	31

Sources:

[a] Based on WF data from Mekonnen and Hoekstra (2011b) and ratios of surface water withdrawal to groundwater withdrawal per region from Ministry of Agriculture (2005a,b). Using the surface/groundwater ratios for withdrawals for estimating the surface/groundwater ratios for blue WFs implicitly assumes that the fractions of return flow are similar for surface and groundwater abstractions.

[b] Mekonnen and Hoekstra (2011b)

[c] Ministry of Environment (2009)

[d] Ministry of Agriculture (2005b)

[e] Own elaboration

In 2005, the total freshwater withdrawal in Tunisia reached 2.65 billion m^3/y, consisting of 0.70 billion m^3/y surface water withdrawal and 1.95 billion m^3/y groundwater withdrawal (Ministry of Environment, 2009). Not all abstracted water evaporates, so that part of the water used remains available in the country for reuse. When we want to compare water use to available water resources, it is better to compare the consumptive water use, i.e. the blue WF, to the available water resources. On a national scale, the total blue WF of crop production was 1.33 billion m^3/y, or 31% of total renewable blue water resources of about 4.26 billion m^3/y. This means that Tunisia experienced 'significant water scarcity' according to international standards. Note that in this analysis we include only the blue WF related to crop production, but this contributes 93% to the total blue WF in the country, so we slightly underestimate water scarcity.

It is estimated that, at national scale, 73% of the blue WF of crop production relates to groundwater consumption, while 27% refers to surface water consumption. The blue WF that specifically relates to groundwater consumption represented 62% of the total renewable groundwater resources, which means that the country was facing severe water scarcity related to groundwater (Table 2-5).

At the regional level, the highest overall water scarcity occurred in South Tunisia (severe scarcity of 78%), followed by Central (significant scarcity of 32%) and North (moderate water scarcity of 23%). In terms of groundwater, all regions of the country experienced severe water scarcity, with a scarcity of 47% in both North and Central and 123% in South Tunisia, where consumptive groundwater use exceeded the available renewable groundwater.

The water scarcity figures presented here are calculated on an annual rather than a monthly basis. As noted by Hoekstra et al. (2012), this may lead to an underestimation of scarcity as experienced in the drier parts of the year, particularly because of the variability in available surface water resources within the year. For estimating groundwater scarcity, the annual approach will generally suffice because of the relatively long residence time and buffering capacity of groundwater systems. Groundwater scarcity figures are possibly underestimated, though, because return flows in groundwater-based irrigation are here assumed to return to the groundwater system from which abstraction took place, while part of the return flow may not return.

2.3.4. Economic water and land productivity at national level

An analysis of water management in a Mediterranean country must have a focus on irrigated agriculture (Garrido et al., 2009). Although irrigated land accounts to only 7% of the total cultivated land in Tunisia (Chahed et al., 2008), it contributes more than 35% to the total production of the agricultural sector and accounts for more than 80% of the total water withdrawal in the country (Ministry of Environment, 2009).

Based on producer prices, Table 2-6 presents the economic water productivity (EWP) and economic land productivity (ELP) of main crops in Tunisia, for both rain-fed and irrigated agriculture. In the case of irrigated agriculture, we distinguish between green and blue EWP and ELP.

In terms of EWP, the average EWP in Tunisian crop production for the listed crops was around 0.32 US$/m^3, which is slightly less than the figure found in a study for Spain by

Garrido et al. (2009), who found an average value of around 0.25 €/m^3, which is equivalent to about 0.35 US$/$m^3$. The average EWP in Tunisian rain-fed agriculture (0.35 US$/$m^3$) was somewhat higher than for irrigated agriculture (0.32 US$/$m^3$). For several of the selected crops, EWP in rain-fed and irrigated production systems were very similar. In the case of carrots and potatoes, however, total EWP was larger in irrigated agriculture than in rain-fed agriculture. For dates and tomatoes, we found the reverse.

In irrigated agriculture, the blue water applied was not always more productive than the green water. For carrots, potatoes and tomatoes, blue EWP in irrigated agriculture was found to be higher than green EWP, but for dates and grapes the reverse was found. While most of the blue water in Tunisia was consumed in dates, grapes, olives and wheat production (Table 2-3), the blue EWP of these crops was low when compared to potatoes and tomatoes, which had the highest blue EWPs, with 0.97 and 1.13 US$/$m^3$ respectively.

In terms of total ELP, oranges, tomatoes and dates had the highest values, with 4040, 3770 and 3080 US$/ha respectively, while barley and olives had lowest values, with 130 and 170 US$/ha respectively.

ELP was higher in irrigated agriculture than in rain-fed agriculture for all selected crops. Given the fact that, on average, EWP in irrigated agriculture was not higher than in rain-fed agriculture, one can conclude that irrigation water is generally not applied to increase EWP (US$/$m^3$) but rather to increase ELP (US$/ha). Enlarging the irrigated area for the listed crops will increase ELP. But, since water is a limiting factor in production, it would be most beneficial to increase irrigated areas only for crops with high EWP and for which the difference between ELP in rain-fed and irrigated agriculture is considerable, like for example potatoes.

Dates and oranges had relatively low EWP (0.23 and 0.58 US$/$m^3$ respectively) as compared to potatoes (0.87 US$/ m^3), but the ELPs for dates and oranges were higher (3080 and 4040 US$/ha respectively) than the ELP for potatoes (2870 US$/ha).

At a national level, EWP figures provide little basis for understanding or explaining current cropping patterns. ELP figures give a better basis, because various of the crops with large production volumes (especially tomatoes, potatoes, oranges and dates) have a relatively high ELP. The main exceptions are wheat, barley and olives, having large production volumes but low ELP (and also low EWP).

Table 2-6. Economic water and land productivities of main crops in Tunisia at national level (1996-2005).

Crop	Economic water productivity (US$/m³)					Economic land productivity (US$/ha)				
	Total (green) EWP in rain-fed agric.	Green EWP in irrigated agric.	Blue EWP in irrigated agric.	Total EWP in irrigated agric.	Average EWP in irrigated & rain-fed agric.	ELP in rain-fed agric.	Green-water based ELP in irrigated agric.	Blue-water based ELP in irrigated agric.	ELP in irrigated agric.	Average ELP in irrigated & rain-fed agric.
Almonds	0.09	0.09	0.09	0.09	0.09	390	380	440	820	430
Barley	0.04	0.03	0.04	0.04	0.04	130	90	90	180	130
Carrots	0.14	0.13	0.19	0.17	0.17	320	270	800	1070	1030
Dates	0.40	0.62	0.11	0.23	0.23	1210	1210	1890	3100	3080
Figs	0.10	0.10	0.10	0.10	0.10	460	442	370	810	720
Grapes	-	0.25	0.17	0.20	0.20	1040	650	830	1480	1480
Olives	0.03	0.03	0.03	0.03	0.03	160	150	130	280	170
Oranges	0.58	0.58	0.58	0.58	0.58	2610	2460	2060	4520	4040
Potatoes	0.80	0.77	0.97	0.88	0.87	1390	1200	1920	3120	2870
Tomatoes	1.26	1.03	1.13	1.07	1.08	2600	1990	1850	3840	3770
Wheat	0.10	0.09	0.12	0.10	0.10	370	290	240	530	370

Source: Own elaboration

2.3.5. Economic water and land productivity at sub-national level

Table 2-7 shows EWP and ELP for the main crops at regional level. North and Central Tunisia had similar EWPs. South Tunisia had lower EWPs for the listed crops except for potatoes. North Tunisia had the highest ELP for all listed crops except for carrots, grapes and tomatoes. Central Tunisia had the highest ELP for carrots and tomatoes, while Central and South had similar ELP for grapes. South had the lowest ELP for all crops except for dates and grapes.

When comparing rain-fed and irrigated agriculture, we find that the ELP of irrigated lands was much higher than the ELP of rain-fed lands for all listed crops. In South Tunisia, which is much drier than North and Central, the blue-water based ELP in irrigated agriculture was higher for all crops than in North and Central, which illustrates the greater importance of irrigation water to yields in the South.

Our conclusion at the national level is valid at regional level as well: enlarging irrigation areas will generally increase ELP, particularly in the South. But primarily in the South, water availability is the key limiting factor in production, not land availability, so optimizing EWP is more advisable than optimizing ELP.

Authorities in Tunisia are using volumetric water pricing systems for irrigation water. There is regional variation of irrigation water prices in Tunisia, from 0.02 to 0.08 US$/m^3 (Frija et al., 2014; Chebil et al., 2010). Blue EWP was around or below the price paid by farmers in various regions, especially for cereals (0.02 to 0.05 US$/m^3 for barley) and olives (0.03 US$/m^3). This supports Frija et al. (2014), who found, in a study on wheat durum in Central Tunisia, that in 50% of the farms the price of one additional cubic metre of irrigation water exceeds the benefit of that additional water.

Table 2-7. Economic water and land productivities of main crops in Tunisia at regional level (1996-2005).

		Economic water productivity (US$/m^3)					Economic land productivity (US$/ha)				
	Crop	**Total (green) WP in rain-fed agric.**	**Green WP in irrigated agric.**	**Blue WP in irrigated agric.**	**Total WP in irrigated agric.**	**Average WP in irrigated & rain-fed agric.**	**ELP in rain-fed agric.**	**Green-water based ELP in irrigated agric.**	**Blue-water based ELP in irrigated agric.**	**ELP in irrigated agric.**	**Average ELP in irrigated & rain-fed agric.**
North	Almonds	0.09	0.09	0.09	0.09	0.09	410	390	420	810	460
	Barley	0.04	0.03	0.05	0.04	0.04	130	90	90	180	130
	Carrots	0.14	0.14	0.19	0.17	0.17	320	270	790	1070	1020
	Date	-	-	-	-	-	-	-	-	-	-
	Figs	0.10	0.10	0.10	0.10	0.10	470	450	360	810	740
	Grapes	-	0.26	0.18	0.21	0.21	1040	710	760	1470	1470
	Olives	0.03	0.03	0.03	0.03	0.03	160	160	120	280	170
	Oranges	0.58	0.58	0.58	0.58	0.58	2580	2490	2030	4510	4090
	Potatoes	0.80	0.77	0.97	0.88	0.88	1430	1220	1900	3120	2910
	Tomatoes	1.25	1.03	1.13	1.08	1.09	2750	2050	1790	3840	3750
	Wheat	0.10	0.10	0.12	0.10	0.10	360	300	220	530	380
Central	Almonds	0.08	0.09	0.09	0.09	0.09	370	350	470	820	410
	Barley	0.04	0.03	0.04	0.04	0.04	110	80	90	180	120
	Carrots	0.13	0.13	0.18	0.17	0.17	290	240	840	1070	1060
	Dates	-	-	-	-	-	-	-	-	-	-
	Figs	0.10	0.10	0.10	0.10	0.10	430	400	420	810	670
	Grapes	-	0.25	0.17	0.19	0.19	-	680	810	1480	1480
	Olives	0.03	0.03	0.03	0.03	0.03	150	150	140	280	160
	Oranges	0.58	0.58	0.58	0.58	0.58	2390	2200	2330	4530	4040
	Potatoes	0.80	0.73	0.97	0.88	0.88	1280	990	2120	3110	2870
	Tomatoes	1.28	1.02	1.13	1.08	1.08	2710	1820	2030	3840	3830
	Wheat	0.09	0.09	0.12	0.10	0.09	310	250	270	520	340

Table 2-7. (continued) Economic water and land productivities of main crops in Tunisia at regional level (1996-2005).

	Crop	Economic water productivity (US$/m³)					Economic land productivity (US$/ha)				
		Total (green) WP in rain-fed agric.	Green WP in irrigated agric.	Blue WP in irrigated agric.	Total WP in irrigated agric.	Average WP in irrigated & rain-fed agric.	ELP in rain-fed agric.	Green-water based ELP in irrigated agric.	Blue-water based ELP in irrigated agric.	ELP in irrigated agric.	Average ELP in irrigated & rain-fed agric.
South	Almonds	0.07	0.07	0.07	0.07	0.07	210	190	630	820	230
	Barley	0.03	0.06	0.02	0.03	0.03	60	100	70	170	80
	Carrots	0.14	0.14	0.19	0.17	0.17	220	280	800	1080	970
	Dates	0.40	0.62	0.11	0.23	0.23	1210	1210	1890	3100	3080
	Figs	0.08	0.08	0.08	0.08	0.08	210	190	620	810	240
	Grapes	-	0.37	0.13	0.17	0.17	-	620	860	1480	1480
	Olives	0.03	0.03	0.03	0.03	0.03	70	80	210	280	80
	Oranges	0.50	0.48	0.48	0.48	0.48	1110	1000	3520	4520	3360
	Potatoes	0.81	0.77	1.00	0.91	0.89	630	1050	2080	3120	2510
	Tomatoes	1.01	0.70	0.89	0.85	1.01	1330	720	3100	3820	1330
	Wheat	0.04	0.05	0.09	0.08	0.07	100	90	440	520	190

Sources: Own elaboration

For South Tunisia it is especially attractive to grow dates, because the climate and growing conditions are very suitable for this crop; dates are not grown in North and Central. The ELP for dates was high as well, but the EWP was not. From the perspective of economic water resources use in South, it is more attractive to grow potatoes, tomatoes and oranges than to grow dates.

The study of economic water and land productivity has a number of limitations that are mostly due to a lack of data. First, we assumed a single producer price of crops for all Tunisian regions, where differences can affect results at regional level. Second, we did not distinguish between prices for rain-fed and irrigated crops. Irrigated crops may have a higher price due to better quality, which would translate into a higher EWP and ELP in irrigated agriculture. Third, we calculated EWP and ELP by multiplying physical productivity and price, instead of the value added per unit of production, implying an overestimation of EWP and ELP. Fourth, we estimated EWP and ELP based on commodity prices, which may not reflect the full costs of those commodities. Finally, we assumed full irrigation in irrigated agriculture, while in reality irrigation may be limited.

2.4. Conclusion

The WF of Tunisian production was 19 billion m^3/y in the period 1996-2005. Green water had the biggest contribution (89%), but there are regional differences. Crops in South generally had a larger total WF and larger blue water fraction than in Central and North Tunisia, caused by differences in climate. South Tunisia is an arid region, explaining why the WF in this region was dominantly blue.

The country suffered significant water scarcity, with a national blue WF of crop production amounting to 31% of the country's renewable blue water resources. South Tunisia experienced severe water scarcity, Central Tunisia significant scarcity and North Tunisia moderate scarcity. For groundwater, all three regions experienced severe water scarcity, with the worst situation in South, where the blue WF resting on groundwater exceeded renewable groundwater resources by an estimated 23%.

91% of the total blue WF of the major crops in the country related to crops produced at blue EWPs below 0.20 US$/$m^3$. Only tomatoes, potatoes and oranges showed larger blue EWP. The smallest blue EWP is found for olives (0.03 US$/$m^3$), one of the major export products of the country.

Among the major crops grown in Tunisia, oranges, tomatoes and potatoes had relatively large EWP and ELP. The same, but to a lesser extent, is true for dates, grown in South only. Relatively low EWP and ELP values are found for wheat, barley, almonds, olives and figs. Irrigation generally increased ELP (US$/ha), but not EWP (US$/m^3). The contribution of blue water to ELP was largest in the dry South.

The scarce Tunisian water resources have mainly been allocated to uses with low EWP; this could be the result of the agricultural policy followed by the Tunisian government. Over the last forty years, Tunisia's agricultural policy focussed on ensuring food security by encouraging the production of staple crops, olive oil and livestock products. This policy intended to ensure prices for those products below international market prices (Ministry of Agriculture, 2002). In general, national agricultural policies, laid down in consecutive socio-economic development plans before and after the 2010 revolution, did not change considerably (Ministry of Agriculture, 2013). Tunisian authorities have started to re-think agricultural policy in relation to water resources management, but no real change in policy can be observed yet. By the end of 1999, Tunisia signed a free trade agreement with the EU, encouraging agricultural imports (Ministry of Agriculture, 2002). Where market conditions exist and staple foods may be externally supplied, farmers can be encouraged to shift to high-value crops and increase EWP (FAO, 2012).

3. Virtual water trade patterns in relation to environmental and socio-economic factors: a case study for Tunisia[2]

Abstract

Growing water demands put increasing pressure on local water resources, especially in water-short countries. Virtual water trade can play a key role in filling the gap between local demand and supply of water-intensive commodities. This study aims to analyse the dynamics in virtual water trade of Tunisia in relation to environmental and socio-economic factors such as GDP, irrigated land, precipitation, population and water scarcity. The water footprint of crop production is estimated using AquaCrop for six crops over the period 1981-2010. Net virtual water import (NVWI) is quantified at yearly basis. Regression models are used to investigate dynamics in NVWI in relation to the selected factors. The results show that NVWI during the study period for the selected crops is not influenced by blue water scarcity. NVWI correlates in two alternative models to either population and precipitation (model I) or to GDP and irrigated area (model II). The models are better in explaining NVWI of staple crops (wheat, barley, potatoes) than NVWI of cash crops (dates, olives, tomatoes). Using model I, we are able to explain both trends and inter-annual variability for rain-fed crops. Model II performs better for irrigated crops and is able to explain trends significantly; no significant relation is found, however, with variables hypothesized to represent inter-annual variability.

3.1. Introduction

Demands for freshwater in agriculture increase, while renewal rates are finite, which makes water a limiting factor in food production in several countries. Water-short countries are increasingly meeting their food requirement through import instead of domestic production (Marianela et al., 2013). By importing food, these countries import 'virtual water', which refers to the water virtually embedded in traded products (Allan, 1998). Importing food shifts local water use to the use of water abroad (Hoekstra and Hung, 2005). Closely linked to the idea of virtual water trade is the concept of water footprint (WF), an indicator of fresh water use from either the consumer or producer point of view (Hoekstra, 2017). The WF has three components: blue, green and grey. The blue WF refers to consumption (net abstraction) of blue water resources (surface and groundwater); the green WF refers to consumption of green water resources

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(rainwater stored in the soil); the grey WF indicates water pollution and is defined as the volume of freshwater that is required to assimilate a load of pollutants, given natural background concentrations and existing ambient water quality standards (Hoekstra et al., 2011). Virtual water trade through food trade thus plays an important role in compensating for the gap between local demand and supply of water-intensive commodities (Antonelli and Sartori, 2015).

A few authors have tried to explain trade patterns in relation to the endowment of production factors, like water availability (the freshwater available for use within country's borders from surface water or groundwater). Yang and Zehnder (2002) presented the case of six southern Mediterranean countries; they demonstrated statistically the significant role that international trade in grains and other agricultural products has played to achieve food security in those countries, and in compensating local water deficits. In a subsequent study, Yang et al. (2003) modelled the relationship between water resources availability and cereal import for Asian and African countries; they showed that the GDP per capita is highly significant in explaining the variations in the level of cereal imports among countries with similar availability of water resources. Kumar and Singh (2005) analysed relations between renewable freshwater availability and net virtual water trade of 146 countries across the world, finding none of them to be significant. Yang and Zehnder (2007) focused on the southern and eastern Mediterranean countries in order to investigate in more detail the relations between water availability and crop trade for different crops. They found that during the last two decades the decline in per capita water resources availability was a dominant factor in explaining the increase in the import of water-intensive crops. Tamea et al. (2014) investigated the drivers of virtual water fluxes associated with international food trade using a gravity-law model over 25 years. They found that GDP and distance are the fundamental controlling factors of virtual water trade, both for import and for export, while the arable land does not give a significant contribution. In a more recent study, Fracasso et al. (2016) investigate the determinants of the bilateral virtual water trade in the Mediterranean basin. The study showed that larger water endowments do not necessarily lead to larger export of water-intensive products.

Over the last decade, many authors estimated the virtual water embedded in traded products (Aldaya et al., 2010; Chapagain and Hoekstra, 2008; Hanasaki et al., 2010; Hoekstra and Hung, 2005). Other authors have estimated the amount of saved water by countries due to their engagement in virtual water trade (Chapagain et al., 2006; Fader et al., 2011; Konar et al., 2013). Some authors made estimates in economic terms quantifying the cost and gain per m^3 as a result of virtual water import and virtual water export respectively (Chouchane et al., 2015; Mekonnen and Hoekstra, 2014; Schyns and Hoekstra, 2014). However, it has not been very common for water sector specialists to consider the relation between water availability in a region and import into and export from that region (Hoekstra, 2013). Furthermore, most virtual water trade studies have been carried out for a specific year, an average over years or a short period of years (Zhuo et al., 2016). The effect of inter-annual variability and trends in environmental, social and economic factors on temporal patterns of virtual water trade has hardly been studied (Zhuo et al., 2016).

The aim of this paper is to analyse trends and inter-annual variability in virtual water trade for Tunisia in relation to environmental and socio-economic factors such as gross domestic product, population, irrigated land, precipitation, and water scarcity. Water scarcity refers here to the ratio of annual blue water consumption (blue WF) to annual blue water availability (total renewable water resources). We choose Tunisia as a case study since it is a severely water-scarce country where water resources are unevenly distributed due to the spatial differences in climate between the north, centre and south of the country (Chouchane et al., 2015). The investigation is made for a selection of main crops based on water productivity (defined as the crop yield over the volume of water consumed), volume of production, and volume of trade. From an economic perspective, a water-scarce country could be expected to trade such that it mitigates the pressure on its domestic freshwater resources; the analysis carried out here will diagnose to which extent this holds for Tunisia. The water footprint is estimated for the selected crops over the period 1981-2010 at a daily basis and spatial resolution of 5×5 arc minute following the method described in The Water Footprint Assessment Manual (Hoekstra et al., 2011). Virtual water trade is quantified at yearly basis. Regression models are used to investigate dynamics in virtual water trade over the years in relation to various environmental and socio-economic factors.

The current paper adds to the existing literature by analysing the dynamics in net virtual water import from a water-scarce country perspective. All other studies focussed on bilateral trade and/or cross-country analysis and did not clearly relate virtual water trade of a country to its internal factors like its blue water scarcity. The reason for undertaking the study is to explore in more detail than previous studies whether we can establish a relation between long-term trends and inter-annual variability in net virtual water import and possibly explanatory factors within the country.

3.2. Methods and Data

In order to analyse the trend and inter-annual variability in virtual water trade, a multiple regression model is used. The regression analysis is performed for selected crops in Tunisia (listed in Table 3-1). We consider the two most consumed staple crops of Tunisia (wheat and barley, which together account for 50% of the daily food supply in kcal per capita in 2010; FAOSTAT, 2015), the two most important cash crops for Tunisian export (olives and dates, which together account for 45% of the total agricultural export value in 2010; FAOSTAT, 2015), and the two crops with highest economic blue water productivity in the country (tomatoes and potatoes; see Chouchane et al., 2015). Wheat and barley are mainly rain-fed and net imported. Olives are rain-fed and dates are mainly irrigated. Both tomatoes and potatoes are mainly irrigated, while tomatoes are exported to a little extent and potatoes are mainly imported (Ministry of Agriculture, 2011). The broad variety of main crops (rain-fed – irrigated, mainly exported – mainly imported, and high and low water productivity) supports the choice of Tunisia as a case study. In order to assess the yearly water footprint of the selected crops during the period 1981-2010, we make use of FAO's soil water balance and crop productivity model AquaCrop (Steduto et al., 2009).

Table 3-1. Average annual production, percentage of irrigated production in total production and net import of the selected crops (1981-2010).

Crop	**Average annual production (10^3 t/y)[1]**	**Percentage irrigated production in total production (%)[1]**	**Net import (10^3 t/y)[1]**	**Economic blue water productivity (US$/m^3)[2]**
Wheat	1100	22	1100	0.12
Barley	390	22	280	0.04
Potatoes	250	98	30	0.97
Olives	720	39	-100	0.03
Dates	95	100	-30	0.11
Tomatoes	690	100	-2.2	1.13

Source: [1] Ministry of Agriculture (2011)

[2] Chouchane et al. (2015).

3.2.1. Regression model

We made similar selections of variables to explain differences in international virtual water trade (VWT) as in previous studies using regression models (Table 3-2). Water availability, GDP and irrigated land are the variables that are commonly used to explain

VWT. In previous studies, water availability referred to blue water availability. Variables representing constraints in green water resources have generally been neglected; however, including green water resources is important in national and regional water resources accounting and in the analysis of water and food relations (Yang and Zehnder, 2007).

In the current study, we adopt a multiple regression approach as in the three previous studies listed in Table 3-2. This gives the opportunity to analyse the variability in the dependent variable (net virtual water import) in relation to possible independent explanatory variables at the same time and yields an understanding of the association of the set of independent variables as a whole with the dependent variable, and the associations between the various independent variables themselves (Marill, 2004). Other studies used gravity-law models in order to investigate drivers of virtual water trade (Fracasso et al., 2016; Tamea et al., 2014). Gravity-law models are used to investigate the spatial patterns of trade, while in the current study we aim to investigate how VWT of one country relates to possible drivers within the country. With respect to earlier multiple regression studies aimed at understanding VWT, a few changes are made here. In addition to GDP and irrigated land, some variables that may explain inter-annual variability will be included. Precipitation is added to cover the green part of the water availability. To check the impact of water scarcity on VWT, a variable of blue water scarcity at national level is integrated into the model. Blue water scarcity is defined as the ratio of total blue water footprint of domestic crop production to total blue water resource availability (Chouchane et al., 2015). The total blue water footprint is estimated by the blue water footprint related to production of the selected crops, dominating the blue WF in Tunisia according to Chouchane et al. (2015). The blue water availability is taken from the Tunisian Ministry of Agriculture (1981-2010a), which reports the amount of water available for exploitation (economically available).

To analyse virtual water trade patterns, we develop multiple regression models to explain net virtual water import (NVWI, the dependent variable) in relation to five selected independent variables: population, GDP, irrigated land, precipitation, and water scarcity level. When we find high collinearity between the independent variables (dependencies between independent variables), we develop different regression models, taking in each model a different subset of the independent variables, minimising collinearity in each model (Table 3-2). The advantage of testing more than one regression model is that we can test a number of hypotheses (presented hereafter).

Table 3-2. Previous and current regression studies and their dependent and independent variables

Study	Type of study	Dependent variable	Independent variables
Yang et al. (2003)	Cross-country study for averages over two 5-year periods	Net cereal import	▪ Renewable fresh water per capita ▪ Sum of arable land and permanent crop land per capita ▪ Irrigated land area per capita ▪ GDP per capita ▪ Annual fertilizer application rate per capita
*Kumar and Singh (2005)	Cross-country analysis for one period of time	Virtual water trade	▪ Renewable water availability per capita ▪ Agricultural water withdrawal per capita ▪ Net gross cultivated land ▪ Net gross irrigated land ▪ GDP per capita ▪ Human Development Index (HDI)
Yang et al. (2007)	Cross-country analysis for two averages of 10 years	Food trade (cereal, oil, sugar, fruit and vegetables)	▪ Water resources availability per capita ▪ GDP per capita ▪ Irrigated area per capita
Current study	One country case study, annual analysis over 30 years (1981-2010)	Net virtual water (NVWI)	▪ Blue water scarcity (blue water footprint / renewable water availability) ▪ Irrigated land ▪ GDP ▪ Population ▪ Precipitation

* In this study variables have been tested jointly and separately.

The multiple regression equation with all variables looks as follows:

$$\text{NVWI} = \alpha + \beta_1 \text{ POP} + \beta_2 \text{ GDP} + \beta_3 \text{ PREC} + \beta_4 \text{ IL} + \beta_5 \text{ BWS} + \varepsilon \qquad \text{(Eq. 3-1)}$$

where NVWI is the net volume of virtual water import expressed in million m^3, POP the size of the country's population in million, GDP the gross domestic product in million (constant 2005) US$, IL the area of irrigated land in 1000 hectare, PREC the precipitation during the (crop-specific) growing period in mm, and BWS the blue water scarcity as a percentage. Parameter α is the constant in the regression, $\beta_1, \beta_2, \beta_3, \beta_4$ and β_5 are the coefficients to be estimated and $\mathcal{E}$ is the error term. The period of study is 1981-2010.

Assumptions for regression modelling such as normality of the distribution of variables, heteroscedasticity and collinearity are checked in order to ensure that the model meets these assumptions and to allow appropriate changes if needed. In the statistical hypothesis testing, we expect a number of linear dependencies to be significant. The main hypothesis is that water scarcity is an important variable in explaining NVWI. Per crop and variable, related hypotheses are as follows:

1. We expect POP, which shows an increasing trend during the period of study (World Bank, 2016; see Appendix Figure A-1a), to explain the trend in NVWI. Population growth is expected to drive consumption and thus have a positive impact on NVWI for all selected crops ($\beta_1 > 0$), so population growth will boost NVWI.
2. We expect GDP, which also shows an increasing trend (World Bank, 2016; Appendix Figure A-1b), to explain the trend of NVWI. Increase of GDP is expected to drive consumption and will have a positive impact on NVWI ($\beta_2 > 0$) for all crops.
3. Precipitation (PREC), which has a clear inter-annual variability for all crops during the period of study (Harris et al., 2014; Appendix Figure A-1c), is expected to drive agricultural production and therefore to have a negative impact on NVWI in case of crops that are predominantly rain-fed ($\beta_3 < 0$), so mainly wheat, barley and olives. It is expected that precipitation could explain a part of the inter-annual variability of the NVWI.
4. Irrigated land (IL), which has inter-annual variability for wheat and barley and an increasing trend for the rest of crops during the period of study (Ministry of Agriculture, 1981-2010b; Appendix Figure A-1d), is expected to have a negative effect on NVWI. In case of irrigation land expansion, a country could produce more, therefore its imports will decline ($\beta_4 < 0$).

The negative impact is likely to be clearer for crops that are mainly irrigated, such as dates, tomatoes and potatoes. IL is expected to explain both trend and inter-annual variability of NVWI.

5. Blue water scarcity (BWS), which shows inter-annual variability and a slight trend during the study period (Appendix Figure A-1e), is expected to positively affect NVWI for all crops in years where BWS is relatively severe ($\beta_5 > 0$). The higher BWS, the greater NVWI in a specific year is expected to be, to release pressure on the water resources.

The sources of the data needed to perform the regressions are summarized in Table 3-3. All data are available as a time series for the 30-year period 1981-2010.

Table 3-3. Overview of data used for the regression.

Input	Sources
Net virtual water import	Own estimation (described in Section 3.2.2)
Gross domestic product	World Bank (2016)
Irrigated land	Ministry of Agriculture (1981-2010b)
Precipitation	CRU TS-3.20 (Harris et al., 2014)
Population	World Bank (2016)
Blue water availability	Ministry of Agriculture (1981-2010a)

3.2.2. Estimating the water footprint of crop production and virtual water trade related to crop trade

This study follows the terminology and methodology as set out in *The Water Footprint Assessment Manual* (Hoekstra et al., 2011), which contains the global standard for Water Footprint Assessment (WFA) developed by the Water Footprint Network. Annual green and blue water footprints (WF) related to the production of the selected crops in Tunisia during the period 1981-2010 were estimated on a yearly basis at grid-level with a spatial resolution of 5×5 arc minute. We did not include the grey WF in this study since we focus on analysing NVWI in relation to blue water scarcity, not water pollution. The selected crops account for 79% of the aggregated green and blue WF of crop production in Tunisia over the period 1996-2005 and for 62% of the total blue WF (Chouchane et al., 2015). The export of olive oil, dates, wheat and tomatoes accounts for 72% of the total crop-related virtual water export (68% for olive oil only) over the period 1996-2005 (Chouchane et al., 2015). The green and blue WFs per unit of crop (m^3/t) were calculated by dividing green and blue crop water use (CWU, m^3/ha) by the crop yield (Y, t/ha) (Mekonnen and Hoekstra, 2011). CWU and Y were simulated per crop per grid per year at daily basis using the user interface and the plug-in of FAO's AquaCrop model version 4.0 (Steduto et al., 2009). The separation of green and blue evapotranspiration (ET) was carried out by tracking the green and blue water in daily soil water balances based on the contributions from rainfall and irrigation, respectively, following Chukalla et al. (2015) and Zhuo et al. (2016).

Table 3-4. Crop characteristics.

Crop	Planting date	Crop Growing Stages				Reference harvest index (HI_0)	Max. rooting depth (m)
		Init.	Dev.	Mid	Late		
Wheat	15th November	30	140	40	30	34%	1.5
Barley	15th November	30	60	60	40	34%	1.3
Potatoes	31st January	25	30	35	30	75%	1.5
Olives	1st March	30	90	60	90	10%	2.5
Dates	15st March	10	110	170	365	20%	4
Tomatoes	15th March	30	40	45	30	63%	1

Sources: Planting dates were taken from local data specific per crop (Ministry of Agriculture, 2000; Ministry of Agriculture, 2007a; Ministry of Agriculture, 2007b; Ministry of Agriculture, 2009; Ministry of Agriculture, 2010a; Ministry of Agriculture, 2010b). Crop growing stages: local data for dates (Ministry of Agriculture, 2000) and Allen et al. (1998) for the rest of crops. Reference harvest index: for wheat from Zwart et al. (2010), for barley from Ouji et al. (2010), for olives and dates from local data (Ministry of Agriculture, 2000; Ministry of Agriculture, 2007b) and for the rest of crops we use the default crop files in AquaCrop. Maximum rooting depth: for olive and dates from FAO (Vanuytrecht et al., 2014) and for the rest of crops as calibrated in AquaCrop.

Before running AquaCrop, inputs on crop calendars, reference harvest indexes and maximum effective rooting depths were carefully selected from different sources in order to reflect Tunisian conditions (Table 3-4), because these are the parameters to which the simulated yield is most sensitive (Vanuytrecht et al., 2014). The selected crops except for olives and dates already have default crop files in AquaCrop. For the case of olives and dates, additional information on initial canopy cover, maximum canopy cover, canopy expansion, canopy decline and plant density was collected from several sources (Ministry of Agriculture, 2000; Ministry of Agriculture, 2007b; Carr, 2013).

Virtual water flows are calculated by multiplying the trade volume for each crop in tonne by its water footprint in m^3 per tonne. Gross virtual water import and export are defined as the amount of water virtually imported by or exported from a country through trade. Net virtual water import is calculated as the net result of gross virtual water import and gross virtual water export. Gross virtual water import is estimated based on crop trade data from Ministry of Agriculture (2011) and a trade-weighted global average of the WF of traded crops from (Mekonnen and Hoekstra, 2011). Gross virtual water export is estimated based on crop trade data from Ministry of Agriculture (2011) and the water footprints of crop production in Tunisia estimated in this study.

The estimation of CWU of growing crops using AquaCrop requires a number of input data, including daily precipitation, daily reference evapotranspiration (ET_0), and maximum and minimum daily temperature. These climatic data were collected with a spatial resolution of 30×30 arc minute at daily basis from CRU TS-3.20 (Harris et al., 2014) and downscaled to 5×5 arc minute grid level assuming homogeneous climate per 30×30 arc minute grid cell. Soil properties at 5×5 arc minute resolution were obtained from the ISRIC-WISE version 1.2 dataset (Batjes, 2012). Data on irrigated and rain-fed harvested area for each crop at 5×5 arc minute resolution were obtained from the MIRCA2000 dataset (Portmann et al., 2010). For the case of crops that are not available in this dataset (olives and dates) we use the 5×5 arc minute map from Monfreda et al. (2008). We derive harvested area at 5×5 arc minute by applying scaling coefficients to the reference MIRCA2000 map to meet the values of the yearly harvested area at sub-national level (planted area in case of wheat and barley) from the dataset collected from the Ministry of Agriculture (1981-2010a). The scaling factor for each sub-national level is applied to all grids within that region. The yearly percentages of rain-fed and irrigated areas specific per crop were obtained from the Ministry of Agriculture (1981-2010a). Since no information about the initial soil moisture in the year 1981 is available, we first run the model for the whole period with an initial soil moisture at field capacity and then assume the average of the soil moisture values for the years 1982-2010 (from the output of AquaCrop) as the initial soil moisture in the year 1981. The results of a second run for the whole period, initialised in 1981 with this derived average soil moisture, are used for the calculation of CWU. Due to lack of data, in calculating CWU using AquaCrop, a few assumptions were made. First, soil water salinity was not taken into account. Second, we do not account for capillary rise of groundwater assuming that groundwater in

Tunisia is too deep to get close to the crops root zone. Third, we assume that there is default field management. Finally, for the tree crops (olives and dates), we assume that we are simulating mature trees, simulating the canopy cover from the date that the tree gets new leaves until the maximum canopy cover and harvesting.

3.3. Results

3.3.1. The Water Footprint of crops

The average annual aggregated green and blue water footprint for the selected crops in Tunisia over the period 1981-2010 was 14 billion m^3/y (Table 3-5). The total WF is dominated by the green component, which contributes 80% to 90% of the total, and 85% on average. The water footprint is largest in the north of the country (Figure 3-1), where mainly wheat and barley are grown, while the largest share of blue WF in the total WF is found in the centre and south of the country, where olives and dates are mostly grown. Among the selected crops, olives had the largest WF per unit of weight (m^3/t), while tomatoes and potatoes had the smallest WF. In terms of the blue WF per tonne, dates had the largest, while potatoes had the smallest value. Regarding the green WF per tonne, olives, barley and wheat had the largest values.

Table 3-5. The average green, blue and total water footprint of the selected crops in Tunisia. Period: 1981-2010.

	Water footprint per tonne of crop (m^3/t)			**Total water footprint (million m^3/y)**		
Crop	**Green**	**Blue**	**Total**	**Green**	**Blue**	**Total**
Wheat	4100	550	4700	4600	610	5200
Barley	5700	660	6400	2200	260	2500
Potatoes	220	120	350	56	31	88
Olives	7100	420	7500	5200	300	5500
Dates	650	5000	5600	62	470	540
Tomatoes	140	180	320	98	120	220
Total*				**12000**	**1800**	**14000**

* Total of the selected crops only.

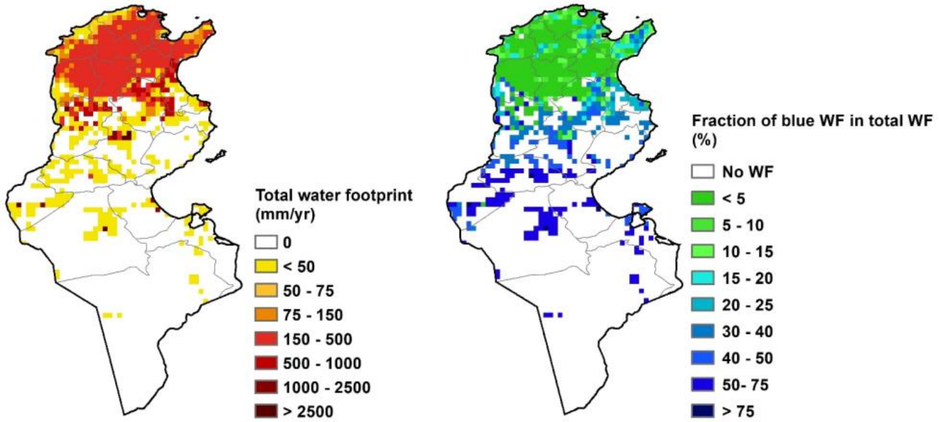


Figure 3-1. The average total water footprint of producing the selected crop in Tunisia the period 1981-2010 and the share of blue water footprint in that total per grid cell.

For the selected crops, olives have the largest share in the total WF in terms of m^3/y, followed by wheat and barley, while potatoes and dates had the smallest share. In terms of blue WF, wheat have the largest share, followed by dates, olives and barley. In terms of green WF, olives have the largest share, followed by wheat and barley (Figure 3-2).

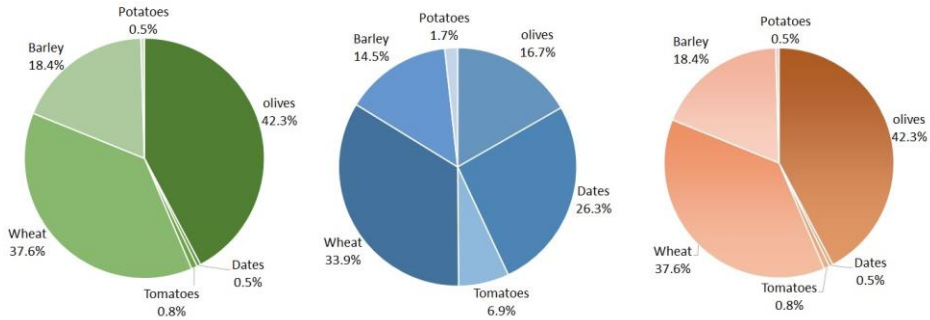


Figure 3-2. The share of crops in the average green, blue and total WF (m^3/ y) in the period 1981-2010

The annual variability of WFs related to the production of the selected crops in Tunisia is presented in Figure 3-3. The green WF contributes most to the total WF and its inter-annual variability. The fluctuation in the total WF is driven by inter-annual climatic variability, and in particular by the length of the cropping season, constrained by precipitation.

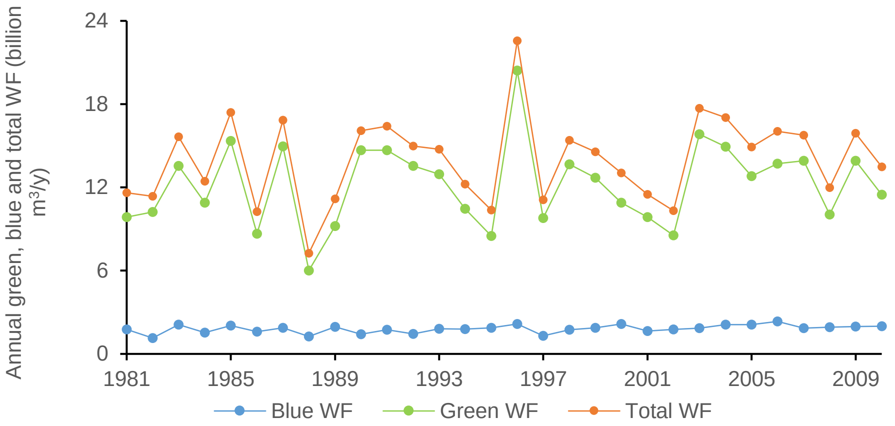


Figure 3-3. Annual variability of green, blue and total WF for the production of the selected crops in Tunisia. Period: 1981-2010.

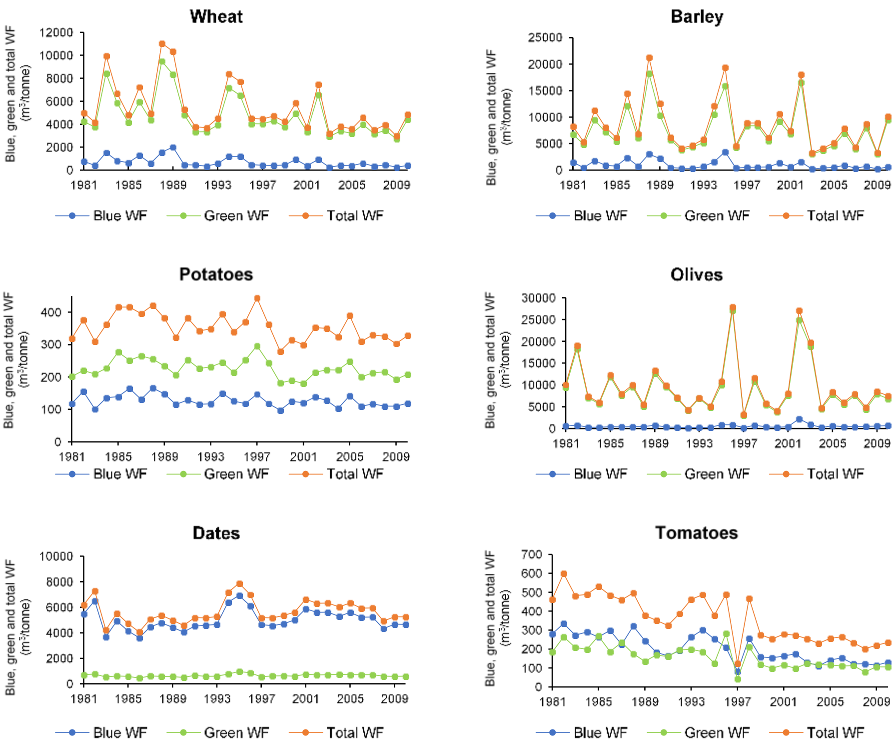


Figure 3-4. The annual green, blue and total water footprint per tonne of crop for the selected crops in Tunisia for the period 1981-2010.

The annual green, blue and total WF per unit of weight is shown in Figure 3-4 for all crops. Water footprints are dominated by the green WF, except for dates and tomatoes where the total WF is dominated by the blue fraction. Tomatoes have the strongest decrease in their WF per tonne during the study period, which can be explained by the increase of tomato yields.

3.3.2. Virtual water trade

The annual net virtual water trade related to trade in the six selected crops of crop products is shown in Figure 3-5. All six show a trend over time: net virtual water imports related to staples crops (wheat, barley and potatoes) are increasing, while net virtual water exports related to cash crops (olive oil, dates and tomatoes) are increasing as well. Dates show the greatest change over the study period. Furthermore, it is shown that virtual water trade related to the three staples crops and olive oil has a high inter-annual variability.

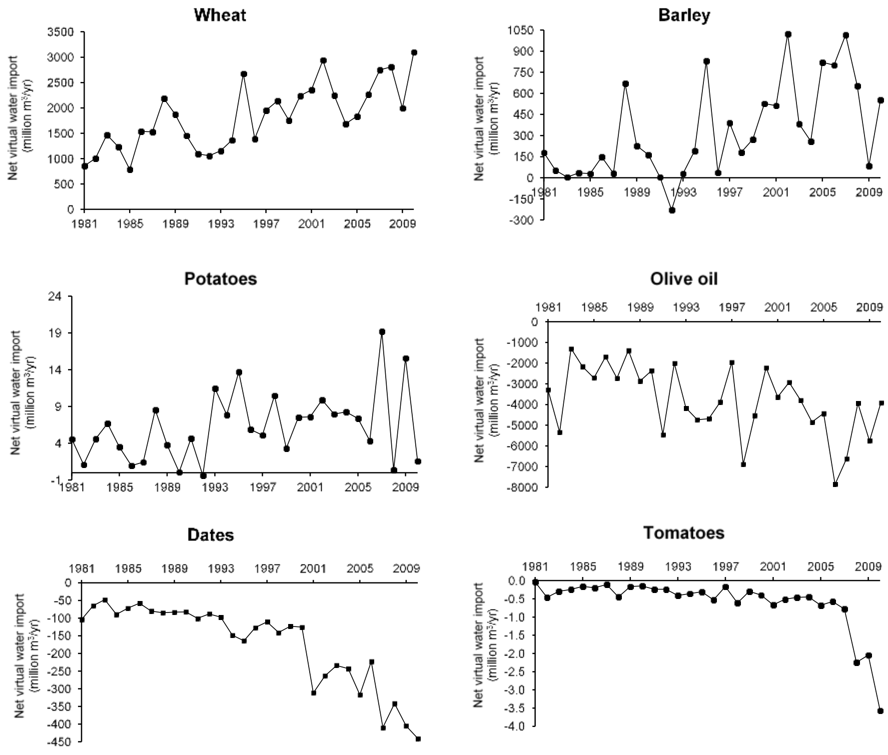


Figure 3-5. Annual net virtual water import related to trade in wheat, barley, potatoes, olive oil, dates and tomatoes (1981-2010).

3.3.3. Regression results

We find high collinearity between two pairs of independent variables, namely (POP, GDP) and (PREC, IL), forcing us to make a choice for variables per pair to perform a meaningful regression. From the statistically allowed combinations we selected two models. The models contain at least one variable hypothesized to explain the trend in NVWI and one variable hypothesized to explain its inter-annual variability. We consider the two models for which the variable combinations provided the best regression performance for all crops (in terms of better fit and higher R^2, which is a statistical measure of how close the data are to the fitted regression line):

Model I:

$$NVWI = \alpha + \beta_1 \, POP + \beta_2 \, PREC + \mathcal{E} \qquad \text{(Eq. 3-2)}$$

Model II:

$$NVWI = \alpha + \beta_1 \, GDP + \beta_2 \, BWS + \beta_3 \, IL + \mathcal{E} \qquad \text{(Eq. 3-3)}$$

The regression results for both models are shown in Table 3-6.

NVWI for the rain-fed and mainly imported staple crops (wheat and barley) correlates to population and precipitation (model I) and to GDP and irrigated area (model II). Both models are plausible (in the sense that they can be explained). Increase in population requires more import of staple crops (positive correlation in the first model). The first model suggests that if the population increases with one million, Tunisia will need an extra NVWI of 400 million m^3 of wheat and an extra NVWI of 170 million m^3 of barley. The fact that precipitation is negatively correlated with NVWI for wheat and barley can be explained by considering that high precipitation in a certain year increases domestic production which leads to a decrease in the need for import. The first model suggests that every increase by 1 mm of precipitation within the crop growing period will decrease the yearly average NVWI of wheat and barley by 3.7 and 1.8 million m^3, respectively. Both precipitation and population have a larger impact on NVWI of wheat than on NVWI of barley.

In the second model, irrigated land negatively correlates with NVWI for wheat and barley, which can be explained by considering that more irrigated land increases domestic production and decreases the need for import. According to the model, an increase in irrigated land by 1000 hectare will reduce the yearly average NVWI of both wheat and barley by 16 million m^3. The positive correlation between GDP and NVWI can be explained by assuming that increased GDP translates in greater demand and thus more import. The second model suggests that increasing the GDP by 1 million will decrease the yearly average NVWI of wheat and barley by 0.05 and 0.01 million m^3, respectively.

NVWI for potatoes is partially (R^2= 16%) explained by model I (population and precipitation). The significance of population for the case of potatoes can be explained the same way as for wheat and barley. However, a one million increase in population will decrease the NVWI of potatoes by 1.55 million m^3, which is a much smaller effect than in the cases of wheat and barley. This is due to the fact that import volumes of wheat and barley are much larger than for potatoes. Precipitation is not significant for the case of potatoes, which can be explained by the fact that potatoes are mainly irrigated crops. Model II does not show significant regression results for potatoes.

Table 3-6. Summary of regression results and statistical tests for models I and II.

Model I	**Coefficient**	**Model II[5]**	**Coefficient**
Wheat		**Wheat**	
Population	400***(8.0)[1] [1.0][2]	GDP	0.05***(5.7) [1.5]
Precipitation	-3.7***(-4.9) [1.0]	Blue water scarcity	440 (0.6) [1.6]
Constant	-640 (-1.3)	Irrigated land	-16*** (5.0) [1.3]
R^2	0.76	Constant	1600 (4.4)
F-statistic	42***	R^2	0.78
Breusch-Pagan[3]	0.71	F-statistic	30***
Durbin-Watson[4]	1.53	*Breusch-Pagan*	0.74
		Durbin-Watson	1.62
Barley		**Barley**	
Population	170*** (4.5) [1.0]	GDP	0.01* (1.9) [1.7]
Precipitation	-1.8*** (-3.2) [1.0]	Blue water scarcity	770 (1.2) [1.7]
Constant	-620 (-1.7)	Irrigated land	-16*** (-3.8) [1.5]
R^2	0.52	Constant	130 (0.5)
F-statistic	15***	R^2	0.58
Breusch-Pagan	0.08	F-statistic	12***
Durbin-Watson	1.63	*Breusch-Pagan*	0.07
		Durbin-Watson	1.76

Table 3-6. (Continued) Summary of regression results and statistical tests for models I and II.

Model I	Coefficient	Model II[5]	Coefficient
Potatoes		**Potatoes**	
Population	1.55** (2.3) [1.0]	GDP	0.001* (2.0) [1.0]
Precipitation	-0.01 (-0.5) [1.0]	Constant	1.91 (0.8)
Constant	-5.9 (-0.9)	R^2	0.12
R^2	0.16	*F*-statistic	3.9*
F-statistic	2.6*	*Breusch-Pagan*	0.09
Breusch-Pagan	0.82	*Durbin-Watson*	2.29
Durbin-Watson	2.18		
Dates		**Dates**	
Population	-79 *** (-7.5) [1.0]	GDP	-0.01* (-2.0) [1.5]
Precipitation	0.10 (0.5) [1.0]	Blue water scarcity	160 (1.5) [1.3]
Constant	510*** (5.2)	Irrigated land	-5.6* (-1.7) [1.6]
R^2	0.68	Constant	75 (1.6)
F-statistic	28***	R^2	0.88
Breusch-Pagan	0.18	*F*-statistic	65***
Durbin-Watson	1.83	*Breusch-Pagan*	0.23
		Durbin-Watson	1.97
Olives Oil		**Olives Oil**	
Population	-680*** (-2.9) [1.0]	GDP	-0.10** (-2.3) [1.3]
Precipitation	-1.20 (-0.3) [1.0]	Blue water scarcity	-3800 (-1.1) [1.3]
Constant	2500 (1.1)	Constant	-150 (-0.1)
R^2	0.25	R^2	0.29
F-statistic	4.5**	*F*-statistic	5.6***
Breusch-Pagan	0.50	*Breusch-Pagan*	0.77
Durbin-Watson	2.05	*Durbin-Watson*	2.14

Table 3-6. (Continued) Summary of regression results and statistical tests for models I and II.

Model I	**Coefficient**	**Model II**[5]	**Coefficient**
Tomatoes		**Tomatoes**	
Population	-0.40*** (-3.7) [1.0]	GDP	-5.0*** (-3.8) [1.9]
Precipitation	0.002 (0.5) [1.0]	Blue water scarcity	1.5 (1.2) [1.3]
Constant	2.4** (2.55)	Irrigated land	-0.04 (-1.3) [1.8]
R^2	0.34	Constant	1.0 (1.3)
F-statistic	7.0***	R^2	0.58
Breusch-Pagan	0.71	*F*-statistic	11***
Durbin-Watson	1.58	*Breusch-Pagan*	0.45
		Durbin-Watson	1.68

***, ** and * denote statistical significance at 99%, 95% and 90% confidence levels. The overall significance of F-static rejects the null-hypothesis and conclude that the model provides a better fit than the intercept-only model.

[1]The t-values, which are the values of the t-statistic for testing whether the corresponding regression coefficient is different from 0, are given between parentheses.

[2] The variance inflation factor (VIF), shown between square brackets, is used for detecting multicollinearity, all VIF are < 3 implying that multicollinearity is not an issue.

[3] The homoscedasticity is tested by the means of *Breusch-Pagan* test, all p-values are higher than 0.05 implying the rejection of the null hypothesis of homoscedasticity.

[4] The serial correlation is tested by the means of Durbin Watson static. All values are within t between the two critical values of 1.5 < d < 2.5 (rule of thumb). Therefore, we can assume that there is no first order linear auto-correlation in our multiple linear regression data.

[5] The variable IL was excluded from Model II for olive oil and potatoes due to the fact that it showed high collinearity with GDP for these two crops while the variable BWS was excluded from model II for potatoes due to high collinearity with IL.

For dates, both models I and II give a statistically strong correlation, with R^2 of 68 and 88% respectively, which means that 68% of the dynamics in NVWI of dates can be explained by the combination of population and precipitation, and 88% by the combination of GDP, irrigated land, and blue water scarcity. However, only model II is plausible, with GDP and irrigated area significantly negatively correlated to dynamics in NVWI (i.e. GDP and irrigated area are positively correlated to net virtual water export). More irrigated land means more production and thus more export. In model II, an increase in irrigated land by 1000 hectare increases the net virtual water export of dates by 5.6 million m^3. Explaining the negative correlation between NVWI and GDP is ambiguous; greater GDP could be the driver of investments and production capacity and thus more export, or the greater GDP could be a result of the greater export. We find a negative correlation between GDP and NVWI (i.e. a positive correlation between GDP and export), but in terms of explanation one could also find a logic for a reverse relation: greater GDP could imply greater domestic consumption and thus reduced export. However, even though statistically significant, Model I doesn't have a real meaning for dates, because the negative sign found for population (representing a positive correlation between population growth and export) is against our first hypothesis and doesn't have a clear explanation; most likely, both population and export of dates have happened to grow in the study period, giving a positive correlation, but without causal relation.

For olives and tomatoes, both models give statistically significant correlations, but none of the models seem plausible in the sense of really explaining something. As in the case of dates, the negative correlation between NVWI and population (positive correlation between export and population) probably reflects the coincidence of two similar trends without causal relation. The negative correlation between NVWI and GDP (positive correlation between export and GDP) could refer to increased exports through increased investments (possible through the higher GDP) or to increased GDP through increased exports. However, one could also argue that higher GDP would go together with higher domestic consumption and thus less olives and tomatoes left for export.

The blue water scarcity variable is found not to be statistically significant in explaining the dynamics in NVWI of any of the six selected crops. Blue water scarcity is only found to have a small positive correlation with NVWI for the case of dates (higher BWS correlated to smaller virtual water export). This can be explained by the high dependence of dates production on blue water. But in combination with other variables, blue water scarcity is found not to be significantly influencing NVWI of dates.

Using the two models for dates and wheat, Figure 3-6 shows the annual predicted and actual NVWI for these two crops over time. We see that for the case of dates, both models I and II predict the trend in NVWI better than the inter-annual variability. For the case of wheat, both models capture both trend and inter-annual variability in NVWI.

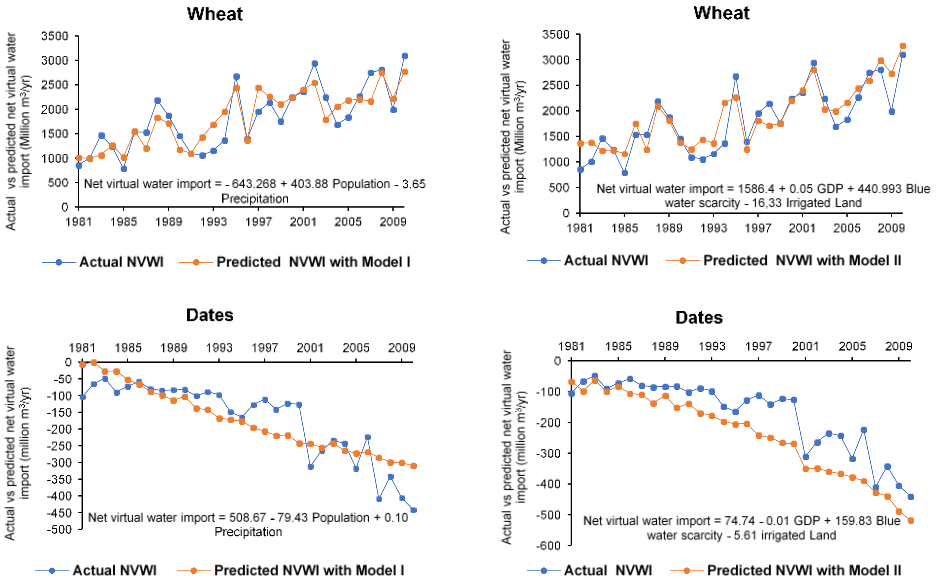


Figure 3-6. Actual versus predicted net virtual water import of wheat and dates.

3.4. Discussion

The current study assessed the green and blue WF of the selected crops in Tunisia. A comparison of the average values for the period 1996-2005 from the current study and reported values in Mekonnen and Hoekstra (2011) is presented in Table 3-7. Except for olives, the values for total (green plus blue) WF from the current study are higher than those from the previous study. Especially for tomatoes, wheat and barley current values are higher by approximately 60, 40 and 35% respectively. Particularly the differences in blue WF are relatively large: the current study gives about 6 times higher values for wheat and barley and 3 times higher for tomatoes. A few methodological differences could explain the different results of the two studies. First, the current study makes use of AquaCrop instead of CropWat for computing CWU, representing water stress on crop yield more accurately. Second, planted area was used for wheat and barley instead of harvested area as in the earlier study. The current study accounts for water use in areas on which cereals are planted but not harvested due to drought-induced yield losses, thus also accounting for unproductive water use. Finally, we use local data to scale harvested/planted area of the reference maps from Portmann et al. (2010) and Monfreda et al. (2008) while in the previous study FAO's dataset was used. Additionally, we scale at sub-national level instead of scaling to country level which is an improvement comparing to the previous study. All methodological differences suggest the current estimates to be more accurate. For olives, the total WF per tonne in the current study was lower than in the previous study, but the blue WF was higher.

Table 3-7. Comparison between estimated green and blue water footprint of the selected crops in Tunisia in the current and a previous study. Period: 1996–2005.

Crop	WF (m^3/t) estimated in current study			WF (m^3/t) from Mekonnen and Hoekstra (2011)		
	Green	Blue	Total	Green	Blue	Total
Wheat	3800	440	4200	2400	70	2500
Barley	5200	490	5700	3600	80	3600
Potatoes	220	120	350	110	120	230
Dates	690	5300	6000	1000	3300	4300
Olives	7200	440	7600	8800	330	9100
Tomatoes	130	160	290	60	50	110

The finding that GDP, population and irrigated land are significant in explaining NVWI dynamics supports the results of Tamea et al. (2014), who studied the drivers of virtual water trade based on gravity laws. Their finding supports also the positive correlation between GDP and virtual water import and export. However, the distance between countries is not included in our study, since we are looking into explaining virtual water trade dynamics of one water-scarce country in relation to its internal factors.

The finding that blue water scarcity was not an influencing factor of virtual water trade in a water-scarce country is similar to the finding of Kumar and Singh (2005) and Fracasso et al. (2016), who found that water endowment and water scarcity level were not driving factors for virtual water trade.

The first hypothesis formulated at the start of this study (Section 3.2.1), on the positive correlation between population and NVWI, holds for the imported staple crops (wheat, barley and potato), but not for the exported cash crops (dates, olive oil and tomato). The second hypothesis, about GDP, is confirmed by model II for the staple crops again, not for the cash crops. Regarding the third hypothesis about the role of precipitation, the results were as expected for wheat and barley, which are rain-fed staple crops, thus sensitive to rainfall in the country. For olives, mainly rain-fed and an exported crop, precipitation was not found to be significant in explaining the dynamics in net virtual water export. Furthermore, precipitation was not significant for crops that are mainly irrigated (dates and tomatoes), which was expected. Regarding the fourth hypothesis, irrigated land has been significant for wheat, barley and dates. This was not expected for wheat and barley, because we expected an impact of irrigated land on mainly irrigated crops. Finally, the fifth hypothesis about the relevance of blue water scarcity, fails for all selected crops.

Dates and olives, the most exported crops in Tunisia, have the highest total WF per unit among the selected crops. Dates have the highest blue water footprint in m^3/t. Additionally, dates are only produced in the south of Tunisia, the region with the highest scarcity level (Chouchane et al., 2015). A remaining question is why a water-scarce country continues producing a blue water intensive crop like dates for export. The selected variables of this study couldn't answer this question; other factors must be the reason. Dates have also a low economic water productivity and from an economic perspective reallocating the water used by dates for growing other crops, with higher water productivity, such as potatoes and tomatoes would be more beneficial (Chouchane et al., 2015).

The current study has a number of limitations that are mostly due to a lack of data. First, in calculating blue water scarcity we use the data on water resources availability from the Tunisian Ministry of Agriculture, which reports the volume of fresh water that is operationally available for use in each year. This measure does not subtract environmental flow requirements, which would be better to get a more appropriate measure for sustainable water availability (Hoekstra et al., 2012). Second, we use precipitation as proxy for green water availability instead of using the soil moisture (rainwater stored in soil) that is a better measure of green water availability. Third, the list of independent variables used in analysing the dynamics in net virtual water import is limited to socio-economic and water-balance-related factors. However, there are other factors that could influence the virtual water trade in a country that are not included in current study, such as: agricultural policies, value of water, international prices, etc. Fourth, the difference between harvested and planted area per crop could only be included for grid cells where a harvested area for that crop existed around the year 2000 according to the databases used (Monfreda et al., 2008; Portmann et al., 2010). Finally, the estimation of WF was limited to the green and blue WF, excluding the grey WF, mainly because of the absence of good data on fertilizer application rates. We assumed no stress related to fertilizer application in calculating the green and blue WFs using AquaCrop.

3.5. Conclusion

In general, the regression exercise has been successful in explaining net virtual water import of staple crops (wheat, barley, potatoes) and less or not at all in explaining net virtual water export of cash crops (dates, olives, tomatoes).

The dynamics of NVWI into Tunisia from 1980 to 2010 for the staple crops wheat and barley can be explained with statistical significance by two different models, one using precipitation and population as explaining variables (model I), and the other using GDP and irrigated land (model II). The models best explained long term trends as well as inter-annual variability for imported staple crops (mainly wheat and barley). For the case of potatoes, only population was found to be significant in explaining NVWI. The increase of population leads to an increasing demand of staple crops and therefore for more import.

For dates, both models I and II give statistically strong correlation with dynamics in NVWI, however only model II is plausible, with irrigated land driving virtual water export. For olives and tomatoes, both models give a significant correlation but do not provide a plausible explanation of NVWI. The relation between GDP and NVWI can go two ways if we think about it (larger GDP thus larger domestic consumption and less export possibility, or larger GDP thus greater investments in domestic agriculture and thus greater export).

Regression models are able to significantly explain both trends and inter-annual variability for rain-fed crops (using model I). For irrigated crops, model II performs better and is able to explain trends significantly; no significant relation is found however with variables hypothesized to represent inter-annual variability.

Blue water scarcity did not appear as a significant factor in explaining NVWI of the selected crops in Tunisia. A water-scarce country as Tunisia may benefit from importing particularly water-intensive staple crops instead of producing them domestically in order to reduce the pressure on local water availability and reduce blue water scarcity. However, this does not turn out to be the case for Tunisia during the period of study. Indirectly, blue water scarcity may have influenced the temporal development of irrigated area that was identified as a significant factor to explain net virtual water import for some crops.

In the period 2010-2050, population in Tunisia is projected to increase by 27% according to the UN medium projection scenario (Melorose et al., 2015), while climate change is expected to bring more inter-annual variability to the precipitation and a decline of about

20% in the annual amount (Mitchell et al., 2004). Based on the role of population and precipitation in explaining NVWI of staple crops, this will have a big impact on the NVWI related to wheat and barley, which represent a big share of the Tunisian diet.

In future studies, other factors could be taken into account, especially for exported crops, such as the price and value added. Furthermore, future research could be done to develop projections of future NVWI based on population growth and climate change scenarios.

Appendix A

The inter-annual variation of the independent variables is shown in Figures A-1(a) to A-1(d). Population and GDP show an increasing trend, the precipitation in growing period for all crops has a clear inter-annual variability, while irrigated land has inter-annual variability for wheat and barley and an increasing trend for the rest of crops.

Blue water scarcity as shown in Figure A-2 has been calculated at yearly basis by dividing the total blue WF in one year by the renewable water availability in the same year. Blue water scarcity shows more inter-annual variability than a trend.

The scaling coefficients applied on harvested area from the MIRCA 2000 dataset and on yield simulated by AquaCrop are shown in Figures A-3 and A-4, respectively. Data on dates harvested were directly taken from local sources since the MIRCA 2000 dataset seems incomplete compared to local data statistics.

Figures A-5(a) to A-5(f) show the average WF of crop production (m^3/t) for the selected crops. For wheat, barley, olive and tomatoes, production was more intense in the north and centre of the country. Potatoes are produced almost in all Tunisia, while dates production is limited to the southern part of the country.

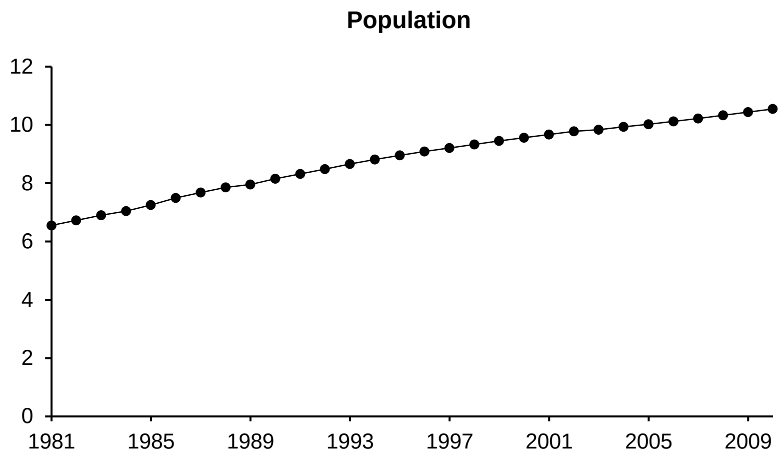


Figure A-1(a). Inter-annual variation of population (million inhabitant / y).

Figure A-1(b). Inter-annual variation of GDP (million US$/y).

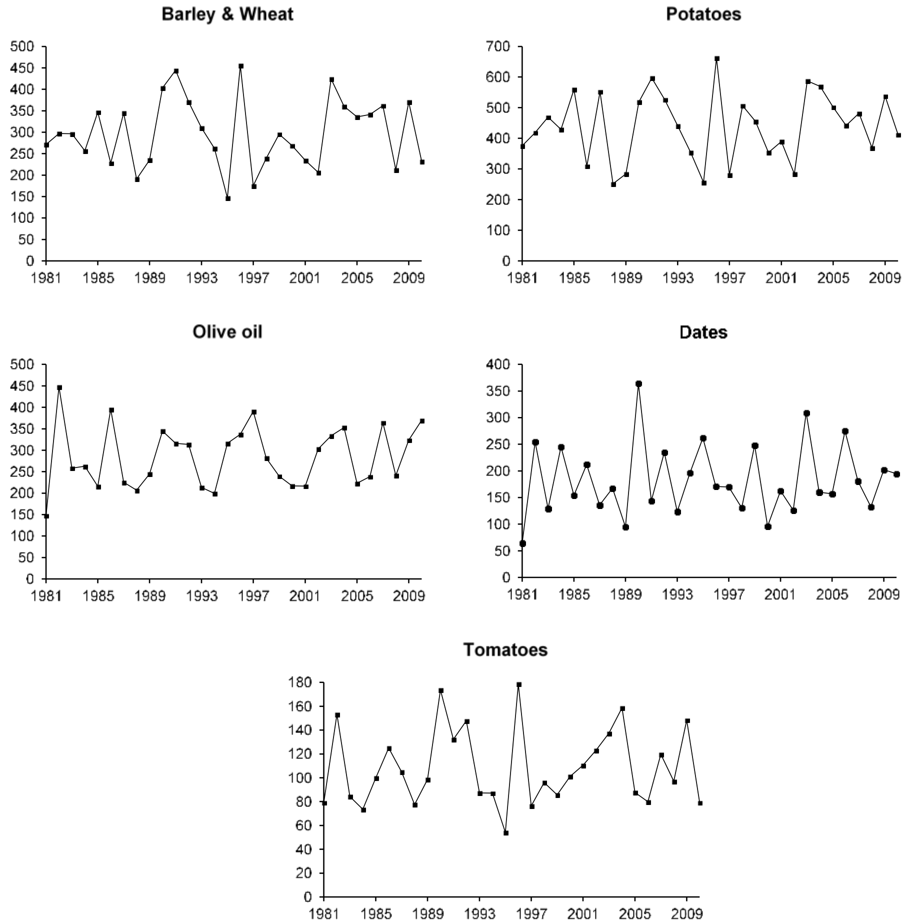


Figure A-1(c). Inter-annual variation of precipitation (mm/y).

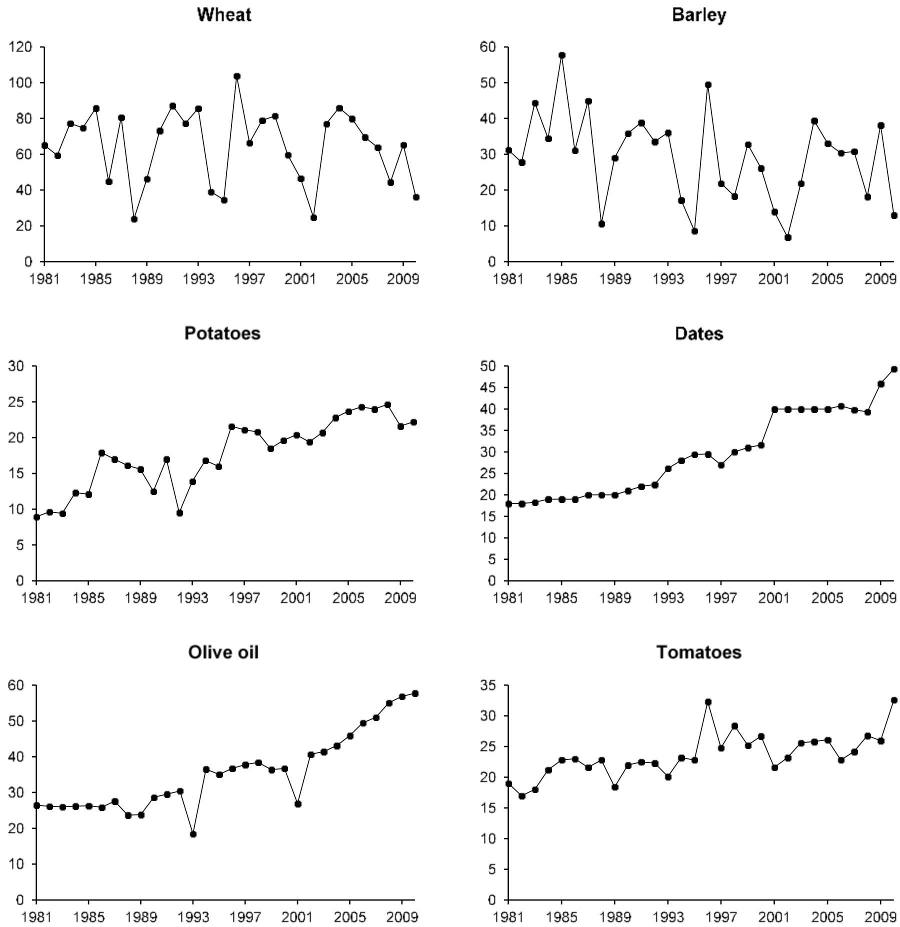
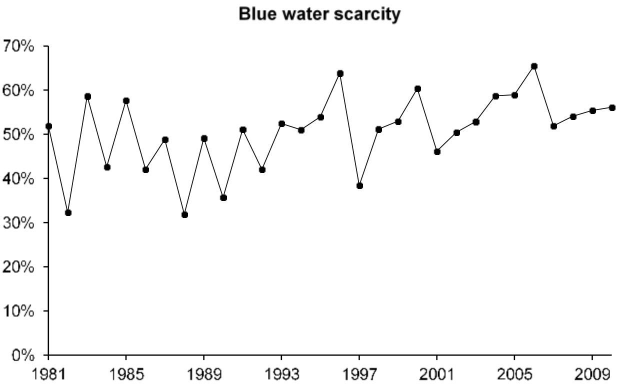
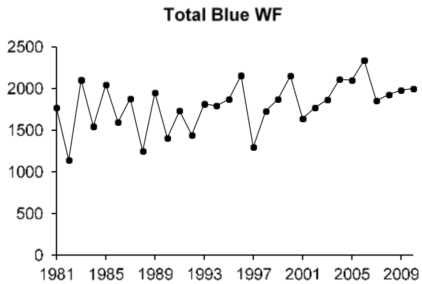


Figure A-1(d). Inter-annual variation of irrigated area (1000 hectare/y).





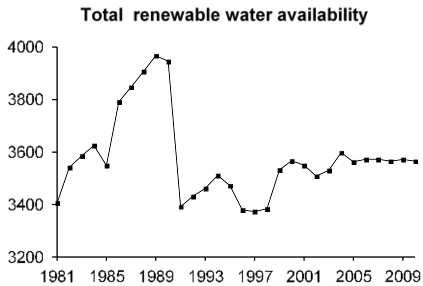


Figure A-2. Blue water scarcity (%), total blue WF (million m^3/y) and total renewable water availability (million m^3/y).

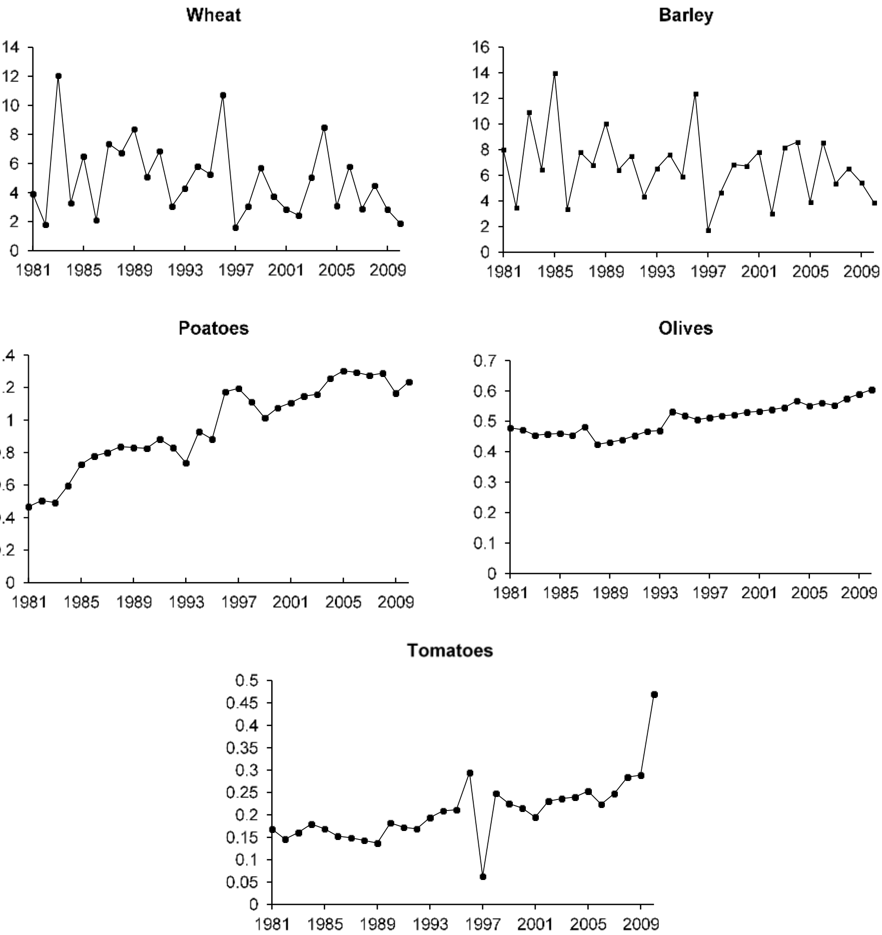


Figure A-3. The scaling coefficients for the harvested area applied on the MIRCA2000 dataset.

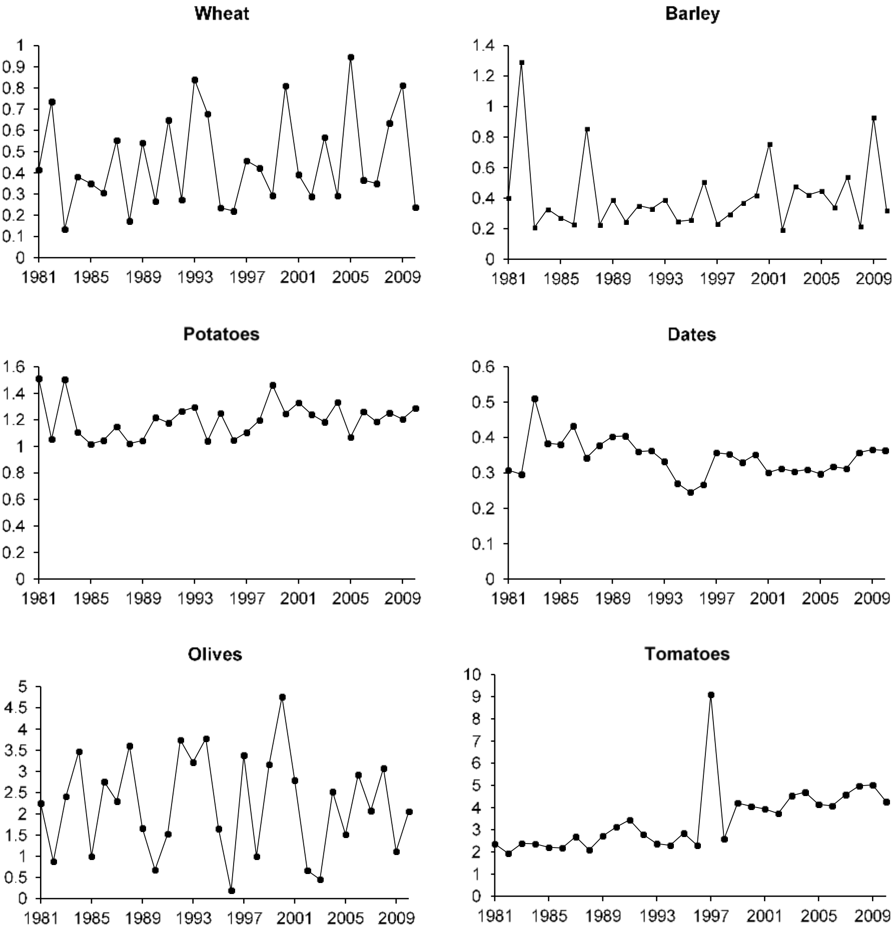


Figure A-4. The scaling coefficients applied to yield as simulated by AquaCrop

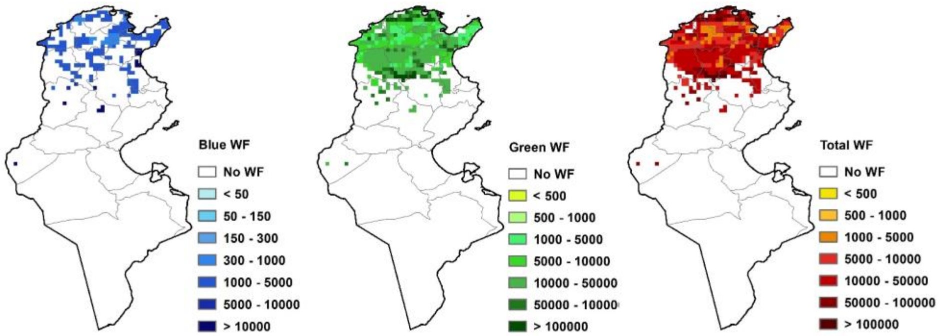


Figure A-5(a). The average blue, green and total WF of wheat production (m^3/t), period 1981-2010.

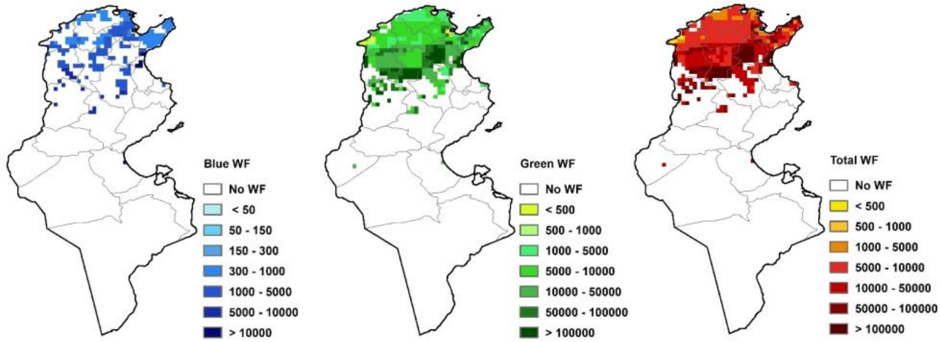


Figure A-5(b). The average blue, green and total WF of barley production (m^3/t), period 1981-2010.

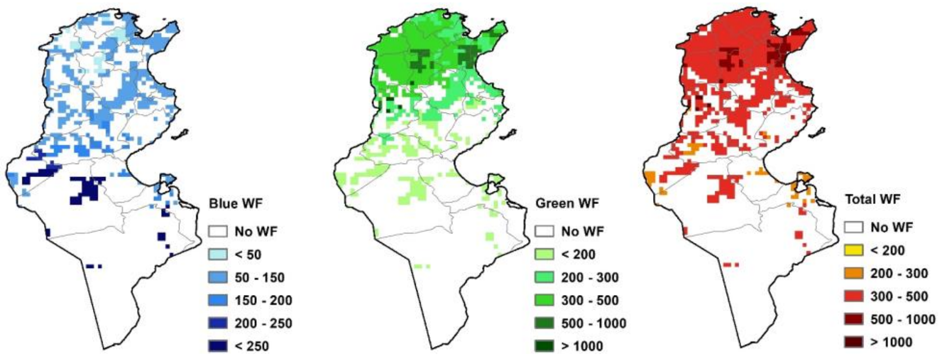


Figure A-5(c). The average blue, green and total WF of potato production (m^3/t), period 1981-2010.

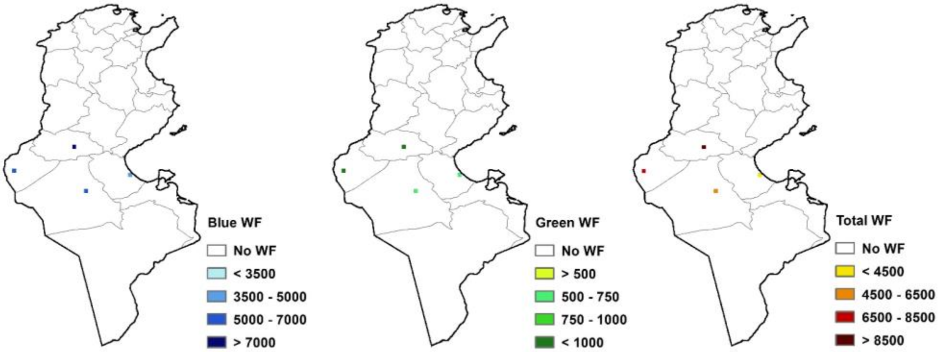


Figure A-5(d). The average blue, green and total WF of date production (m^3/t), period 1981-2010.

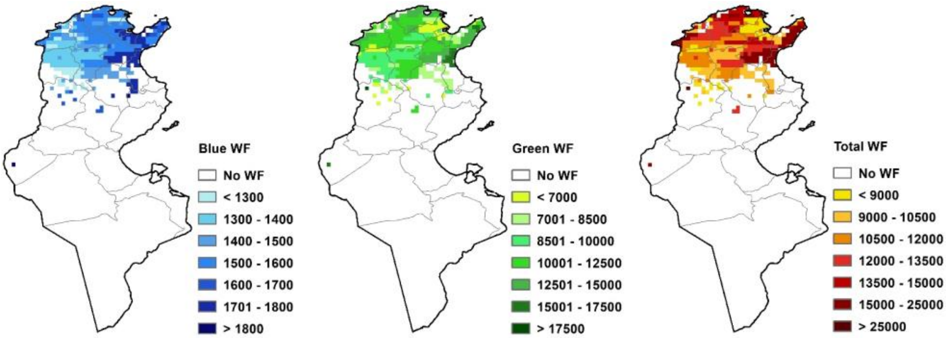


Figure A-5(e). The average blue, green and total WF of olive production (m^3/t), period 1981-2010.

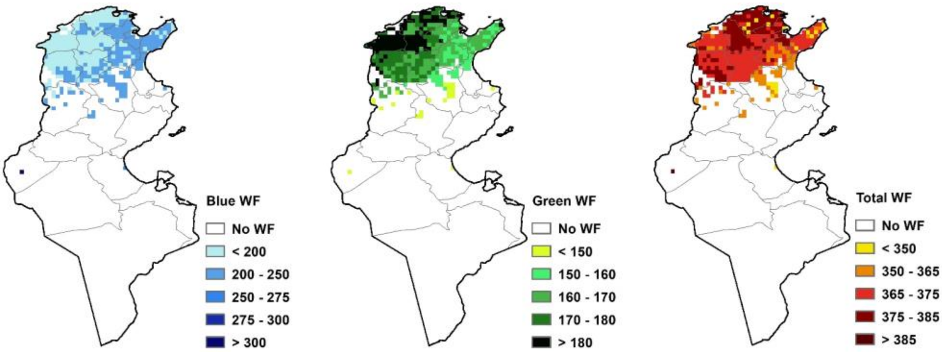


Figure A-5(f). The average blue, green and total WF of tomato production (m^3/t), period 1981-2010.

4. Expected increase in staple crop imports in water-scarce countries in 2050[3]

Abstract

Population growth paired with growing freshwater scarcity in various parts of the world will reduce the potential of food self-sufficiency in many countries. Today, two thirds of the global population are already living in areas facing severe water scarcity at least one month of the year. This raises the importance of addressing the relationship between water availability and food import in water-scarce countries. Net import of staple crops (including cereals, roots, and tubers) is analysed in relation to water availability per capita for the period 1961-2010, considering five decadal averages. The relation found is used, together with the population growth scenarios from the United Nations, to project staple crop imports in water-scarce countries for the year 2050. As a result of population growth in water-scarce countries alone, global international trade in staple crops is projected to increase by a factor of 1.4 to 1.8 towards 2050 (compared to the average in 2001-2010), in order to meet the staple food needs of the 42 most water-scarce countries in the world.

4.1. Introduction

Water scarcity is a major challenge in the coming decades, particularly for food production (Davis et al., 2017). An estimated 4.0 billion people are living under conditions of severe water scarcity for at least 1 month of the year, 3.3 billion for at least 3 months, and 1.8 billion at least half a year (Mekonnen and Hoekstra, 2016). The increasing population and the changing pattern of water availability that results from global warming reduce the potential of sufficient food production in many countries (Godfray et al., 2010). Given that already today most water-scarce countries rely on food imports, the question is how much the water-scarcity driven global demand for food imports may grow.

According to the medium projection of the United Nations, the world population will reach 9.7 billion by 2050 and exceed 11 billion by 2100 (United Nations, 2015). Africa and Asia will have the highest population growth between 2015 and 2050, with projected population increases of 52% and 17%, respectively (United Nations, 2015). These two continents already have the highest undernourishment prevalence levels, viz. 20% and

[3] This chapter has been published as:
Chouchane, H., Krol, M.S. and Hoekstra, A.Y. (2018) Expected increase in staple crop imports in water-scarce countries in 2050. Water Research X 1, 100001.

12% of their total population, respectively (FAO et al., 2015). Population growth and climate change are major variables affecting future water demand and scarcity (Vörösmarty et al., 2000) and thus food security (Hanjra and Qureshi, 2010). While the green revolution helped in the past to feed a growing global population, there is a growing concern about the future (Gilland, 2002). Climate change is expected to aggravate the situation and threatening food security by altering spatial and temporal rainfall patterns, reducing crop yields in various vulnerable regions (Parry et al., 2004) and lowering food security particularly in sub-Saharan Africa and South Asia (Schmidhuber and Tubiello, 2007). However, it has been widely acknowledged that when it comes to water scarcity, population growth is a bigger driver than climate change (Arnell, 2004; Gerten et al., 2011; Schewe et al., 2014; Vörösmarty et al., 2000).

Food insecurity in water-scarce countries can partially be mitigated through improving water productivity in crop production (Kate et al., 2013), through better irrigation and agricultural management practices (Chukalla et al., 2015; McLaughlin and Kinzelbach, 2015; Tilman et al., 2011). Food import may be another solution to fill the gap between demand and supply from domestic food production in many countries and especially in water-scarce countries. Such imports go along with virtual water import (Allan, 1998), externalising water consumption. Virtual water trade could be a solution to cope with physical water scarcity if water-scare countries import their water-intensive food needs from water-abundant countries (Aldaya et al., 2010; Chapagain and Hoekstra, 2008; Hoekstra and Hung, 2005).

During the past decade, a growing number of virtual water trade studies has become available (Antonelli and Sartori, 2015; Hoekstra, 2017), some focussed on quantification and others on analysing policy implications, but surprisingly little effort has been made to correlate virtual water import to water scarcity. Most notably, for countries in Asia and Africa, Yang et al. (Yang et al., 2003) investigated the relationship between cereal import and per capita water resources availability for a period of ten years. A water scarcity threshold of about 1500 m^3/y per capita was identified, below which cereal import of a country increases exponentially with the decline of per capita water availability. Above it, no direct relationship was found between cereal import and water endowment. A weakness of this study was that staple crops other than cereals, like starchy roots and tubers (e.g. cassava, potatoes, sweet potatoes and yam) were not included, while many developing countries depend on these other staple crops. Besides, it is more meaningful to consider staple food import in terms of kcal per capita than in terms of kg per capita. No follow-up has been given after this valuable initial study from Yang et al. (Yang et al., 2003), while good insight into water-scarcity driven demand for food import could be useful to project future needs of the many countries that face water scarcity already today.

This chapter aims to study the relation between import of staple foods (including cereals, roots and tubers) and water scarcity with a long-term and global perspective. The net import of staple crops in kcal/y per capita is analysed in relation to water availability per capita for the period 1961-2010, considering five decadal averages. The relation found is used together with the low, medium and high population growth scenarios from the UN (United Nations, 2015) to project future staple crops import in water-scarce countries for the year 2050. Additionally, we investigate the uncertainties related to the three population scenarios and related to the regression analysis.

4.2. Methods and data

Countries have been selected based on three criteria. The selection contains countries with a maximum average blue water availability of 5000 m^3/y per capita in the period 2001-2010. Excluded are countries for which more than 50% of total domestic supply of staple crops is for feed, seed, processing or other uses and not for food supply. Excluded are also countries with a population smaller than 500.000 inhabitants in the year 2010. This resulted in a selection of 42 countries.

In total, 13 staple crops were selected: barley, cassava, maize, millet and products, oats, potatoes, rice, rye, sorghum, soybeans, sweet potatoes, wheat and yams. The selection is based on the main produced, consumed and traded crops globally. The selected crops account to 45% of total crop quantity produced, 50% of total food supply in kcal/day per capita, 44% of total crop import and 43% of the total crop export quantities in 2010 (FAO, 2015).

Gross imports and exports of staple crops in t/y per country for the period of study (1961-2010) were taken from the FAOSTAT database (FAO, 2015). Net imports of staple crops in kg were converted into kcal using conversion rates (Appendix Table B-1). Per country, average net import of staple crops per decade was calculated, for each of the five decades in the study period and net import per capita was calculated using decadal average population data from the UN (United Nations, 2015).

The total blue water availability per capita per country was derived from the FAOSTAT database (FAO, 2015). Water availability is taken as the total renewable water resources (TRWR), which is the sum of internal and external renewable water resources of a country (FAO, 2003). We added, per country, the yearly produced desalinated water. Although desalinated water is mostly used in other sectors than agriculture, it helps in reducing the overall pressure on freshwater resources. In this way, countries that use desalinated water may dedicate a larger share of their fresh water to agriculture. The TRWR values, representing 30-year averages (1961-1990), are assumed to be constant per country over the period of study and divided by decadal averages of population to obtain average water availability per capita per decade.

Regression modelling is used to analyse the relation between the blue water availability per capita (y) and the net import of staple crops per capita (x). Statistical model testing proved a logarithmic relation to yield the best fit amongst standard functional options for the relation. The model was extended to the equation $y = \mathrm{a}\log x + b + \sum_{i=2}^{42} c_i \cdot d_i$ including country-specific biases c_i, implemented by including country-specific dummy variables d_i. Statistically, country-specific biases were significant for most countries and the model extension improved the fitness of the model (higher R^2).

The medium population growth scenario of the UN (United Nations, 2015) is used to obtain projections for the decrease in blue water availability per capita per country for the year 2050. The projected net import of staple crops per capita per country in 2050 (y) based on the blue water availability per capita per country for the year 2050 (x), is estimated using the equation $y = \mathrm{a}\log x + b + \sum_{i=2}^{42} c_i \cdot d_i + e_i$, whereby the values for a, b and c are taken according to the best-fitting curve for the last decade (2001-2010), and e_i is the difference between the curve and the value in the last decade for each country.

The impact of two types of projection uncertainties are estimated. The uncertainty in population growth is studied by considering UN's low and high population growth scenarios (United Nations, 2015). The uncertainty in the shape of the regression curve is estimated by varying the regression slope coefficient within its 95% reliability interval.

4.3. Results

4.3.1. Past blue water availability and net import of staple crops (1961-2010)

Changes in blue water availability and net import of staple crops from the period 1961-1970 to the period 2001-2010 for 42 selected countries show a clear general trend (Figure 4-1). There is a continuous increase in net import of staple crops per capita with decreasing water availability per capita. The effect of decreasing water availability per capita on food import becomes more pronounced when water availability becomes less. The best fitting regression curve through all data points – when also including the

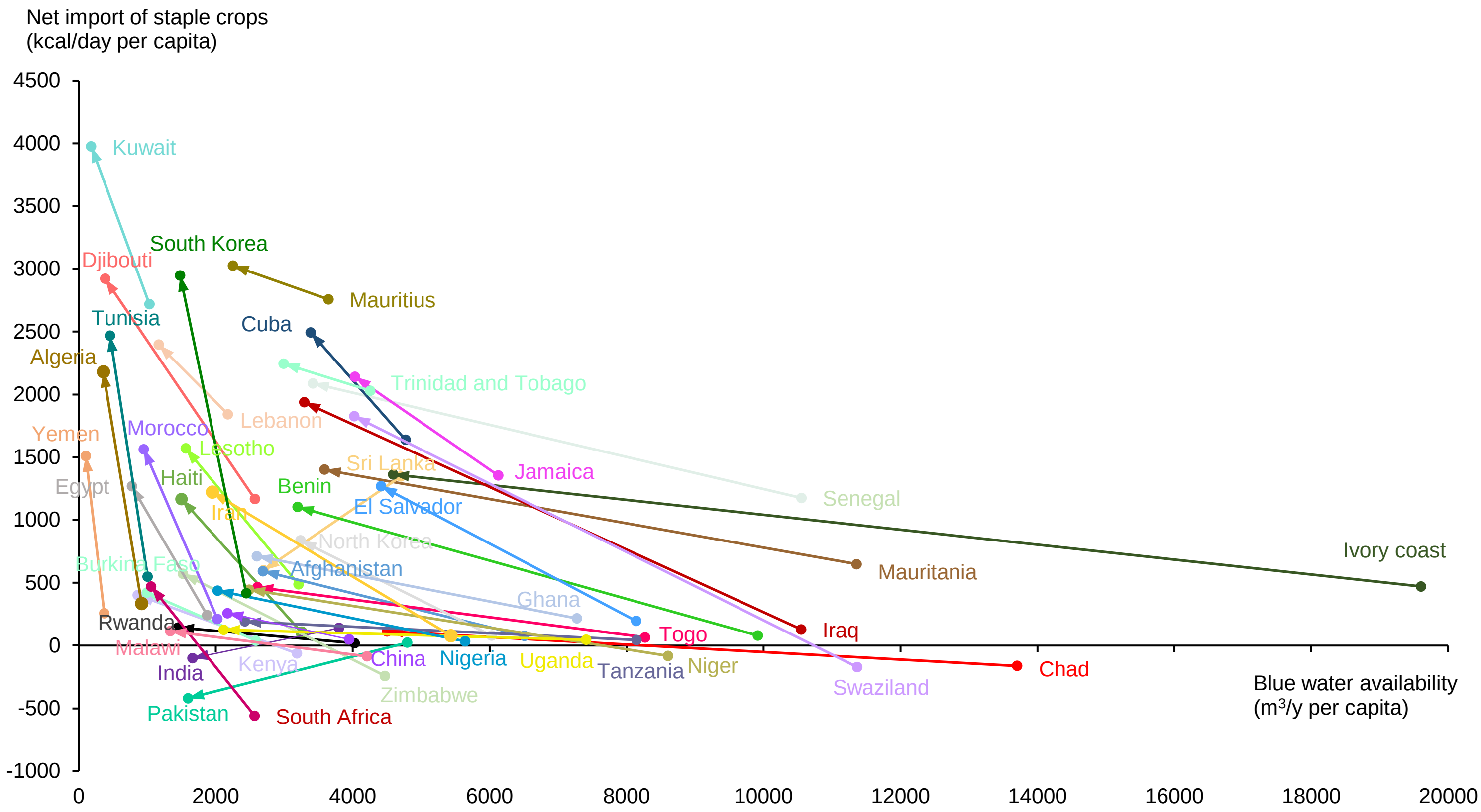


Figure 4-1. Change in the average blue water availability per capita and net import of staple crop per capita for the selected countries, from the period 1961-1970 to the period 2001-2010.

data points for all five decades considered – follows a logarithmic shape as shown in the Appendix (Appendix Figure B-1).

India, Pakistan and Sri Lanka were the exceptions to the general pattern, with decreasing net staple food imports. While Sri Lanka remained a net importer of staple crops, India and Pakistan shifted to become net exporters. Some countries shifted from being net exporters of staple crops during the first decade to net importers in the last decade. This is the case for Chad, Malawi, Niger, Kenya, South Arica, Swaziland and Zimbabwe, where a growing domestic demand of staple crops due to population growth affected the countries' capability to export and increased their import of staple crops.

While Figure 4-1 shows changes in blue water availability and staple crops import per capita between the initial and last period exclusively, hiding intermediate points in time, Fig 4-2 shows all data for the five decadal averages for a few selected countries. This exemplifies that some countries shift gradually over time, while other countries show a bit more erratic behaviour. Each country has its specific underlying story.

Benin exhibits a progressive decrease in blue water availability and increase in the net import of staple crops consistent with the shape of the global regression curve. For Iraq, there was a drop in net staple food import between the 1980s and 1990s. The economic sanctions imposed on Iraq (1990-2003) after the Gulf war limited the imports of staple crops (Alnasrawi, 2001), which was partially compensated with increased national production but mostly resulted in reduced food supply. Food supply dropped by 32% between 1990 and 1991 and is still recovering two decades later (FAO, 2015). Kuwait has seen a large decline in its food supply as well, dropping by 25% between 1989 and 1990 and reaching its minimum in 1991 with 1900 kcal/day per capita (FAO, 2015). Opposite to Iraq, the food supply of Kuwait recovered already in 1995 (Appendix Figure B-2). Therefore, Kuwait's food supply drop is not visible in the decadal averages appearing in Figure 4-2, showing the country to follow the steep part of the regression curve at very low water availability. Cuba follows the trend of the global regression curve, but had a dip in net import of staple crops in the 1990s. The collapse of the Soviet Union resulted in deceasing Cuban imports due to its economic dependence (Perkins, 1993). Cuban imports of maize and wheat dropped by 85% and 36%, respectively, between 1990 and 1991 (FAO, 2015). Food supply decreased from 1989, reached its lowest level in 1993, and started to recover in 1996. In the 2000s, imports increased again. The data for Egypt show an anomaly for the 1990s as well, as shown by Yang el al. (Yang et al., 2003) as well. The expansion in irrigated land of about 35% during that period increased the production of cereals, resulting in a decreased import of cereals per capita while total import continued to increase (Yang et al., 2003). The import dependency ratio of staple crops has decreased from 40% in average between the 1970s and 1980s to an average of 29% between the 1980s and 1990s (FAO, 2015). Yang et al. (Yang et al., 2003) expected that the proportion of the imported cereals in the per capita consumption will again increase in the future as the country's water use is reaching its limit. This is confirmed in Figure 4-2, which shows that one decade later, the net import of staple crops regained its increasing trend while the import dependency ratio of all staple crops has increased to 31% in average between the 1990s and 2000s. In the same way, Lebanon's import dependency ratio has dropped by 4% due to an increased production of barley, potatoes and wheat between the 1990s and 2000s, which explains the decrease in the net staple crops import for the last decade.

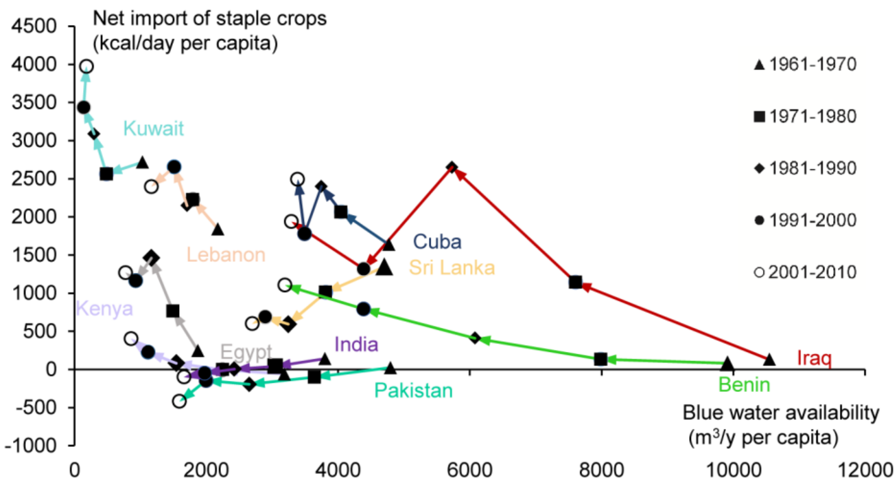


Figure 4-2. Trajectories of decadal average blue water availability per capita and net import of staple crop per capita over the 1960s, 1970s, 1980s, 1990s and 2000s for ten selected countries.

For the case of Kenya, a country that was net exporter of staple crops until 1977, the import dependency ratio has jumped from 3% during the 1960s to over 27% in the period 2001-2010 to keep pace with the growing domestic demand of staple crops. This is also partially explained by Kenya's policy to promote the production of cash crops (Gow and Parton, 1995) such as coffee and tea. While staple crop production has in average dropped by 25% between the 1960s and 1990s, coffee and tea production have grown by almost 1.5 and 5 times, respectively, in the same period (FAO, 2015).

India, Pakistan and Sri Lanka are the only three countries that do not follow the main trend line. Both India and Pakistan have even become a net exporter of staple crops despite their increasing water scarcity. In India, changes in trade mainly concern increases in rice and wheat exports. The green revolution has boosted the productivity in agriculture: average wheat yield increased from 0.8 t/ha in the 1960s to about 3 t/ha in the 1990s, and average rice yield doubled (FAO, 2015). India thus succeeded to become food self-sufficient, but at the expense of a rapid increase in the appropriation of water resources, leading to severe water depletion in many places (Mekonnen and Hoekstra, 2016). The intensive use of irrigation from groundwater and surface water has caused groundwater degradation in many districts of Haryana and Punjab, the largest contributing states to rice and wheat production in India (Singh, 2000). The irrigated area had been continuously increasing to maintain the food self-sufficiency policy. Similarly, Pakistan was one of the first beneficiaries of the green revolution in the 1960s, with intensification through the introduction of high-yielding varieties in wheat and rice, and the application of irrigation and fertilisers (Ali and Byerlee, 2002). This has led to negative environmental impacts such as salinization, overexploitation of groundwater, physical and chemical deterioration of the soil, and pest problems (Gupta and Seth, 2007). Sri Lanka, a country with decreasing imports during the five-decade period, is an example of a country with an agricultural policy aiming for food self-sufficiency in all crops and especially in the production of rice, the country's main staple crop. Due to a combination of high-yielding varieties, paddy expansion and increased use of irrigation and fertilizer, rice production in Sri Lanka has risen to meet almost 100% of its domestic demand (Davis et al., 2016). The production of rice has increased by a factor of almost five between 1961 and 2010 while the average yearly yield has increased from 1.9 t/ha to over 4 t/ha during the same period (FAO, 2015).

4.3.2. Projected blue water availability and net import of staple crops (2050)

In 2050, when assuming UN's medium population growth scenario, the net import of staple crops in kcal/day per capita is projected to increase for almost all selected countries except for Cuba where net import of staple crops is projected to drop slightly (by 2%). India and Pakistan, the only net exporting counties of staple crops in the list in the period 2001-2010, will become net importers of staple crops by 2050 (Table 4-1). Water availability per capita will decrease in all countries (Figure 4-3). Between the baseline 2001-2010 and the year 2050, the total net import of staple crops for the selected countries in kcal/day is projected to increase by a factor 2.5 for the medium population growth scenario (or a factor 2.2 for the low, or a factor 2.8 for the high population growth scenario) (Appendix Table B-2). In the period 2001-2010, the gross import of staple crops in the selected countries in kcal/year corresponded to 34% of the world total gross export (FAO, 2015). From this, we compute that towards 2050 the overall global trade in staple crops should increase by a factor of 1.4, 1.6 or 1.8, according to the low, medium and high population growth scenario, respectively, in order to meet the increased staple food needs of these most water-scarce countries (Appendix Table B-3). The largest expected relative increases in the net import of staple crops (by a factor of around 30 in the medium population growth scenario) are found for Chad, Malawi and Uganda, that were nearly self-sufficient in the 2000s, but grow fast and are becoming water scarcer rather quickly.

The projected net imports of staple crops in 2050 as shown in Table 4-1 and Figure 4-3 are subject to both uncertainty in population growth and uncertainty in the shape of the regression curve. Uncertainty in population growth directly translates in uncertainty in future water availability per capita; indirectly, this results in uncertainty on staple food import per capita, because food imports depend on water availability per capita following the regression curve. The uncertainties in the projected net import of staple crops per country related to population growth range between 57 and 99 kcal/day per capita, while the uncertainties coming from the curve-shape range from 1 until 805 kcal/day per capita (Table 4-1). The total uncertainty related to the regression analysis at 95% level of confidence ranges from 219 to 275 kcal/day per capita (Appendix Table B-4). The horizontal extent of each quadrilateral in Figure 4-3 reflects the uncertainty in population growth; the vertical extent follows from the upper and lower estimates for the regression curve shape parameters. The shape of the quadrilateral is country dependent. For countries with blue water availability exceeding 1500 m^3/y per capita in 2050, the quadrilateral is wider horizontally; this means that for those countries the uncertainty in population growth mainly translates in moving horizontally in the graph, and less vertically, because the regression curve has a low slope in this range and uncertainties in the slope are moderate. For countries with less than 1500 m^3/y of blue water availability per capita, the quadrilateral gets stretched more vertically; this means that the uncertainties in the curve shape become greater than the uncertainties related to population growth. For some countries (China, Cuba, El Salvador, Jamaica, Mauritius, South Korea, Sri Lanka and Trinidad and Tobago), the data point for 2001-2010 is within the surface of the quadrilateral for 2050. This is due to the fact that following the low population scenario, there will be a decrease in the inhabitants of these countries by 2050.

Table 4-1. The average net import of staple crops (2001-2010) in kcal/day per capita, the projected net import of staple crops for the year 2050, and the uncertainties in the projected net import due to uncertainties in population growth and in the shape of the regression curve.

Country	Average net import of staple crops (2001-2010) in kcal/day per capita	Projected net import of staple crops in 2050 with the medium population growth scenario in kcal/day per capita	Uncertainty in projected net import	
			due to uncertainty in population growth (+/-)	due to uncertainty in the shape of the regression curve (+/-)
Afghanistan	593	1187	81	13
Algeria	2182	2553	75	697
Benin	1104	1820	73	93
Burkina Faso	421	1238	70	364
Chad	113	997	67	255
China	258	279	72	93
Cuba	2492	2432	73	139
Djibouti	2921	3218	78	693
Egypt	1268	1763	81	473
El Salvador	1269	1320	97	285
Ghana	712	1310	75	2
Haiti	1164	1463	88	249
India	-100	180	86	208
Iran	1222	1414	84	140
Iraq	1937	2736	73	274
Ivory coast	1363	2060	93	235
Jamaica	2141	2148	93	235
Kenya	403	1103	76	419
Kuwait	3973	4614	75	749
Lebanon	2396	2655	86	353
Lesotho	1570	1879	99	233

Table 4-1. (continued) The average net import of staple crops (2001-2010) in kcal/day per capita, the projected net import of staple crops for the year 2050, and the uncertainties in the projected net import due to uncertainties in population growth and in the shape of the regression curve.

Country	Average net import of staple crops (2001-2010) in kcal/day per capita	Projected net import of staple crops in 2050 with the medium population growth scenario in kcal/day per capita	Uncertainty in projected net import	
			due to uncertainty in population growth (+/-)	due to uncertainty in the shape of the regression curve (+/-)
Malawi	114	973	71	262
Mauritania	1399	2062	70	151
Mauritius	3026	3041	84	75
Morocco	1564	1819	81	430
Niger	446	1632	57	19
Nigeria	438	1177	65	109
North Korea	837	924	82	111
Pakistan	-419	75	80	215
Rwanda	143	740	80	248
Senegal	2088	2912	68	123
South Africa	471	684	95	394
South Korea	2947	2988	66	269
Sri Lanka	599	643	85	16
Swaziland	1826	2161	98	221
Tanzania	190	1075	72	31
Togo	464	1193	76	1
Trinidad and Tobago	2245	2240	85	71
Tunisia	2468	2668	78	666
Uganda	126	1036	69	88
Yemen	1510	2096	81	805
Zimbabwe	573	1152	84	230

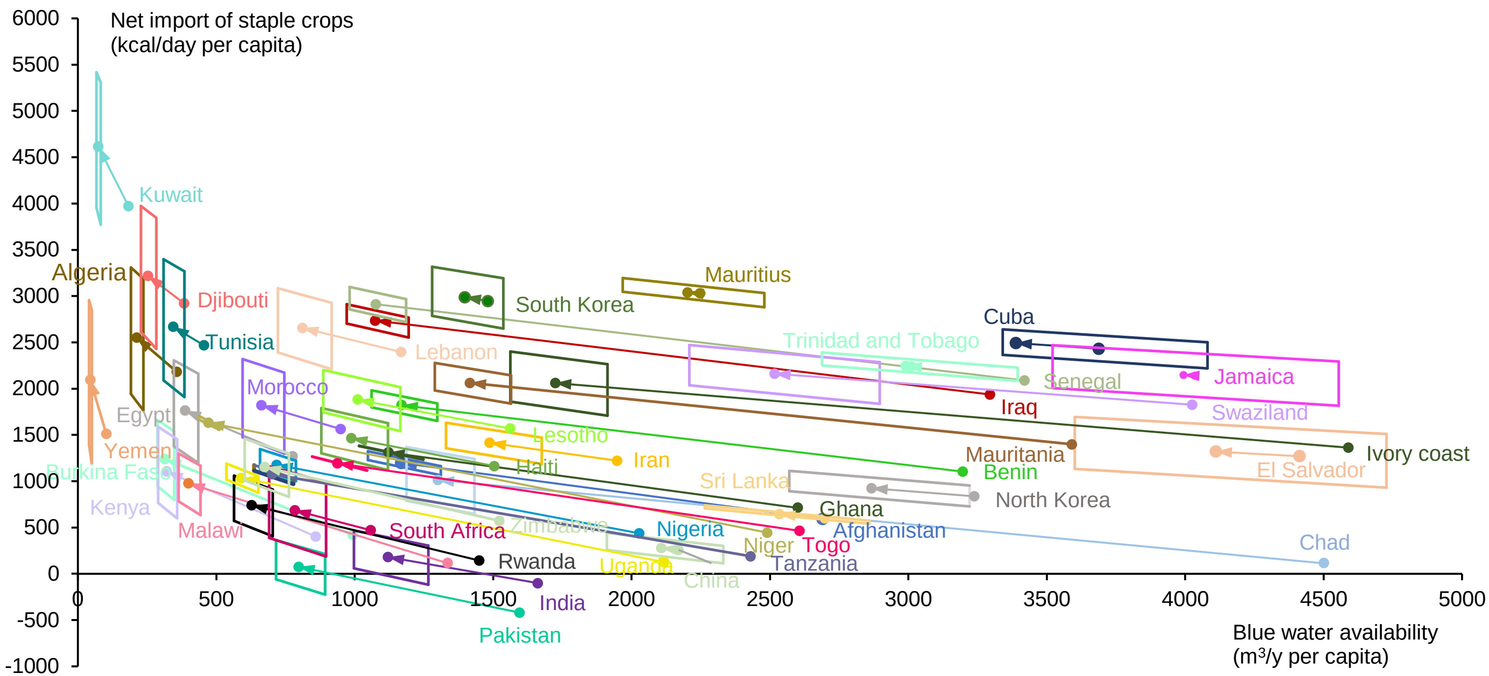


Figure 4-3. Projection of staple crop imports per country from the 2000s (the lower right dot for each country) to 2050 (the upper left dot). The upper left dot per country is the central projection for 2050 using the medium population scenario and best-fitted curve; each quadrilateral reflects the uncertainty in the central projection as a result of uncertainties in population growth and the shape of the regression curve. The left and right sides of the quadrilateral correspond to the high and low population projection, respectively, and the upper and lower sides of the quadrilateral correspond to the high and low values of the regression slope coefficient (reflecting the 95% reliability interval).

4.4. Discussion

One of the limitations of the study is the focus on blue water availability and exclusion of green water resources. Blue and green water scarcity are naturally related though, so that it is unlikely that countries with low blue water availability per capita are rich in green water resources to produce food. Indeed, in the selected countries staple crops are mainly irrigated, which indicates that rain-fed (green-water-based) agriculture alone is insufficient. Nevertheless, given the relevance of scarcity of green water (Schyns et al., 2015), we recommend future study to further evaluate the potential effect of increasing green water scarcity, or overall green-blue water scarcity, on international food trade.

Another limitation is that total blue water availability per country has been taken as a 30-years average for the period 1961-1990, not accounting for climatic changes where they may have occurred. However, when expressed per capita, the effect of population growth on water availability per capita will be by far dominant in all countries. While precipitation has a high interannual variability, the linear trend for the global average precipitation from the Global Historical Climatology Network during 1901–2005 is statistically insignificant (Bates et al., 2008). Given the strong population growth in all countries considered, both in the past and the future, trends in national water availability per capita will anyhow be dominated by changes in population. However, including climatic changes, particularly for the future, can possibly refine our results.

We found that although a person normally needs 2000 to 2500 kcal/day, there are countries that are importing over that need from only staple crops already in the period 2001-2010, such as Djibouti, Kuwait, Mauritius and South Korea. Algeria, Lebanon and Tunisia will join these countries by 2050. We may question the validity of our projection method in this range, because once all staple food needs are imported, the precise amounts will probably rather depend on other factors, like dietary preferences and food waste.

Although the regression curve representing the historical relation between net national staple-crop import and national water availability per capita that was used to project net national staple-crop imports in 2050 gets very steep when water availability per capita gets very low, the steepness in the curve is represented by a high number of data points. Two countries are projected for 2050 to fall outside the bounds of the data used to fit the regression, namely Kuwait and Yemen. The results for these two countries should thus be taken with extra caution. The projected net import of staple crops for these two countries together represents less than 3% of the total net import of staple crops of the selected countries, so it does not affect the overall results of the study.

Although war and other socio-political factors have impacted trade of some countries in specific periods (e.g. the economic sanctions for Iraq in the 1990s), there will be no change in the study results if we exclude those countries from the analysis. This has been checked by carrying out the regression analysis without Afghanistan, Iraq and Chad for the relatively recent period 2000-2010. This did not cause significant changes affecting the main conclusions of the paper.

The list of the 42 most water-scarce countries includes some countries that are major exporter of one or more specific types of staple crops. In 2010, China, for instance, was an important exporter of millet, potatoes, rice, sorghum, sweet potatoes and yams; Egypt exports potatoes, rice and sweet potatoes; Ghana and Jamaica export yams; India exports maize, millet, rice and sorghum; Iran exports potatoes; Kenya sorghum; and Mauritius cassava. For rice, exports from the selected water-scarce countries were responsible for 24% of global export in 2010. India, the largest rice exporter, already faces major environmental issues related to the overuse of water resources, particularly groundwater depletion (Gupta and Seth, 2007), which threatens the sustainability of its future production and limits its exporting ability.

Based on an analysis of 42 water-scarce countries over five decades of change we found a significant logarithmic shaped relation between net staple-food import in kcal/day per capita and blue water availability per capita. Most of the selected countries follow the regression curve shape, with an exception for a few anomalously-behaving countries such as India, Pakistan and Sri Lanka. The curve found here has a similar shape as the relation found earlier by Yang et al. (Yang et al., 2003), although they considered different countries, less staple crops and a shorter period of change, and looked at kg of import rather than kcal.

4.5. Conclusion

Using the regression curve and UN population growth scenarios, we project that, compared to the average in the baseline period 2001-2010, the total net import of staple crops for the selected countries in kcal/y will increase towards 2050 by a factor of 2.2, 2.5 or 2.8, for the low, medium and high population growth scenario, respectively. This means that global trade in staple foods should increase by a factor of 1.4 to 1.8 in order to meet the staple food needs of the 42 most water-scarce countries in the world. This finding is of broader interest than for the water-scarce countries only; it indirectly influences all other countries involved in staple crop trade. Amongst others, this raises the question of where additional amounts of staple crops in the future could be sourced from, and what additional water and other environmental impacts that may have in these other countries.

Appendix B

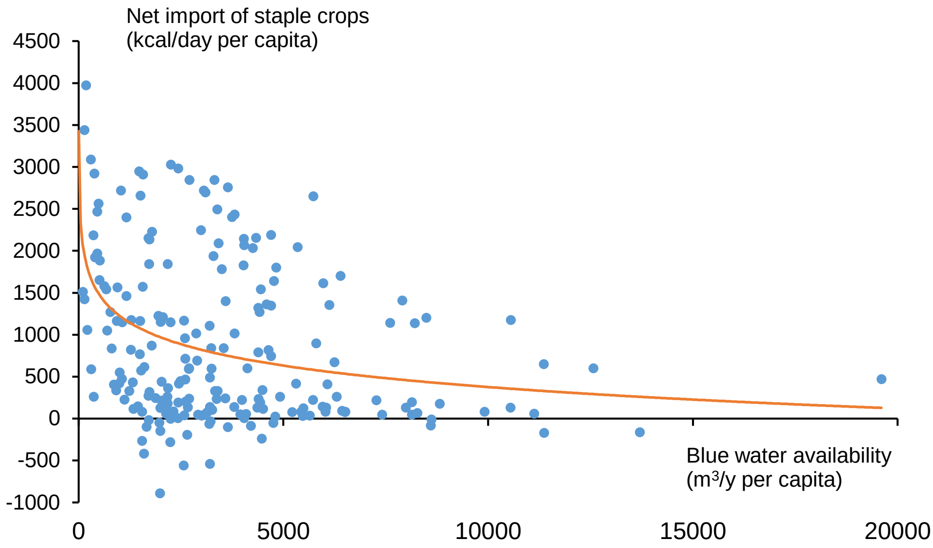


Figure B-1. The fitted regression curve for the relation between the average blue water availability per capita and the net import of staple crops per capita for the selected 42 counties, with average data for the periods 1961-1970, 1971-1980, 1981-1990, 1991-2000, and 2001-2010 (five data points per country).

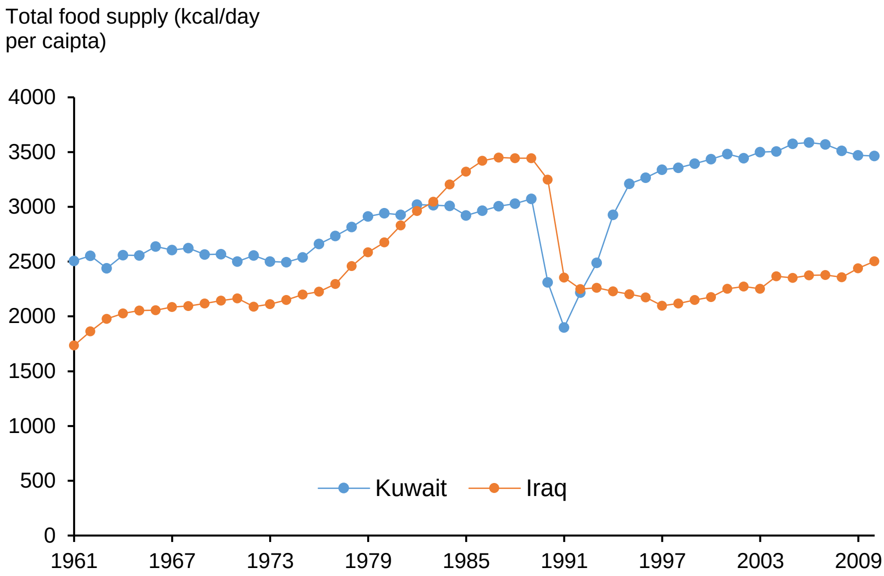


Figure B-2. The total food supply (kcal/day per capita) of Iraq and Kuwait from 1961 till 2010. Both countries had a drop in their food supply between 1990 and 1991. Kuwait's food supply has recovered to its levels before the crisis while Iraq is still recovering its food supply after two decades.

Table B-1. Ratios to convert net staple crops import from tonne to kcal. Source FAO (FAO 2001).

Crops	**kcal/t**
Wheat	3330
Barley	3332
Rice	3600
Maize	3560
Soybeans	3350
Oats	3850
Sorghum	3430
Yams	900
Cassava	1090
Potatoes	700
Sweet potatoes	970
Rye	3190
Millet	3400

Table B-2. The average net import of staple crops (2001-2010) in kcal/day and the projected net import in 2050 (both in absolute terms). Increases at aggregate (regional) level in terms of a percentage are shown between brackets.

Country	Average net import of staple crops (2001-2010) in kcal/day	Projected net import of staple crops in 2050 in kcal/day		
		Low population growth scenario	Medium population growth scenario	High population growth scenario
Algeria	73403627	125317954	144134592	164213102
Benin	9190238	35487307	41039587	47010745
Burkina Faso	5767426	45282767	52983794	61292700
Chad	1156026	29624584	35039563	40909741
Djibouti	2287708	3321963	3817215	4339578
Egypt	95953606	225945677	266395245	310814234
Ghana	15458876	55608046	65615419	76450294
Ivory coast	25059086	87347681	100527984	114746186
Kenya	14469611	87756244	105381362	124711626
Lesotho	3039597	4613072	5612744	6727715
Malawi	1484307	35696847	41981988	49427559
Mauritania	4470855	14508538	16598265	18827522
Mauritius	3701177	3278051	3797534	4362222
Morocco	47855747	67507239	79468789	92485975
Niger	6161593.283	104978252.2	117866665.7	131530680.6
Nigeria	62132016.37	403818145.2	469078619.6	539171149.7
Rwanda	1322201	12609277	15673163	19240427
Senegal	23942934.98	93446237.2	105484514.8	118208428.4
South Africa	22916689	33716727	44856677	57572318
Swaziland	2048842	3208637	3872944	4602186
Tanzania	7574402	123802126	147359985	173074441
Togo	2633114.175	15705597.3	18707391.66	21989182.12
Tunisia	25118009	31162847	35958306	41096282
Uganda	3602919	88939542	105573480	123648228
Zimbabwe	7533032	27950407	34107596	40932461
Africa	**468283640**	**1760633767 (276%)**	**2060933423 (340%)**	**2387384983 (410%)**

Table B-2. (continued) The average net import of staple crops (2001-2010) in kcal/day and the projected net import in 2050 (both in absolute terms). Increases at aggregate (regional) level in terms of a percentage are shown between brackets.

Country	Average net import of staple crops (2001-2010) in kcal/day	Projected net import of staple crops in 2050 in kcal/day		
		Low population growth scenario	Low population growth scenario	Low population growth scenario
Afghanistan	14531396.84	55049492.42	66442391.89	78859579.3
China	337819482.2	252115304.2	376238909.7	518245613.6
India	-115798546	140551272	307123147.9	504157516.2
Iran	86180028.2	108864039	130371566.3	154179394.7
Iraq	53141057.75	200053367.6	228849673.8	259825063.6
Kuwait	9588944.005	24164233.77	27332903.39	30713937.35
Lebanon	9394004.242	12749338.47	14897251.31	17241332
North Korea	19960646.45	20140484.37	24856555.01	30077491.81
Pakistan	-65064622.73	-1577069.764	23330950.75	52362703.4
South Korea	140803145.8	134420348.4	151181541.2	168660678.9
Sri Lanka	11719972.01	10284559.99	13398828.77	16860989.24
Yemen	31510181.89	84640767.57	98886137.01	114257244.7
Asia	**533785691**	**1041456138 (97%)**	**1462909857 (174%)**	**1945441545 (264%)**
Cuba	28042161.42	22046839.52	25145748.95	28555115.09
Haiti	10869528.14	17200575.15	20755913.03	24656108.16
Jamaica	5744292.197	4880741.499	5820581.881	6877726.699
Trinidad and Tobago	2918633.378	2467176.055	2892888.017	3356511.966
Caribbean	**47574615**	**46595332 (-2%)**	**54615132 (15%)**	**63445462 (33%)**
El Salvador	7552439	6782198	8434237	10316708
Central America	**7552439**	**6782198 (-10%)**	**8434237 (12%)**	**10316708 (37%)**
Total selected countries	**1057196385**	**2855467435 (170%)**	**3586892648 (239%)**	**4406588698 (317%)**

Table B-3. The average gross import of staple crops (in the period 2001-2010) in t/y and Gcal/y and the single effect of increased future import of staple crops in the 42 selected water-scarce countries on overall global trade (keeping all other variables equal).

	Average import of staple crops (2001-2010)		Gross import of staple crops in 2050 under increased demand in water-scarce countries alone (Gcal/y)		
	t/y	Gcal/y	Low population growth scenario	Medium population growth scenario	High population growth scenario
Selected water-scarce countries	148218500	460500	1042200	1309200	1608400
Rest of the world	283993200	894500	894500	894500	894500
World	432211700	1355000	1936770	2203740	2502929
Share of the selected water-scarce countries in global food import	34%	34%	54%	59%	64%

Source: Trade data for 2001-2010 from FAO (2015). Projected import for selected countries in 2050 based on the totals from Table B-2 (multiplied by 365 to convert daily to annual values).

Table B-4. Statistical output (from SPSS) using per country bias (dummy 1-41), the lower and upper bound for B with 95% confidence interval and the total uncertainty in the regression analysis.

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.	95.0% confidence interval for B		The total uncertainty in the regression analysis
	B	Std. Error	Beta			Lower bound	Upper bound	
(Constant)	6034.082	451.240		13.372	0.000	5143.212	6924.953	
Log (blue water availability)	-712.595	65.320	-0.675	10.909	0.000	-841.555	-583.634	
dummy 1	1559.927	266.572	0.250	5.852	0.000	1033.643	2086.212	263.1
dummy 2	1281.239	233.790	-0.205	-5.480	0.000	-1742.805	-819.674	230.8
dummy 3	505.087	221.514	0.081	2.280	0.024	67.759	942.415	218.7
dummy 4	-646.754	228.656	-0.104	-2.828	0.005	-1098.184	-195.324	225.7
dummy 5	608.297	245.889	0.097	2.474	0.014	122.846	1093.748	242.7
dummy 6	-3.289	234.804	-0.001	-0.014	0.989	-466.856	460.277	231.8
dummy 7	-421.196	236.497	-0.067	-1.781	0.077	-888.105	45.713	233.5
dummy 8	-460.281	237.489	-0.074	-1.938	0.054	-929.148	8.586	234.4
dummy 9	646.876	234.318	0.104	2.761	0.006	184.269	1109.483	231.3
dummy 10	450.022	276.373	0.072	1.628	0.105	-95.613	995.657	272.8
dummy 11	-582.617	237.024	-0.093	-2.458	0.015	-1050.567	-114.667	234.0
dummy 12	1726.010	264.093	0.276	6.536	0.000	1204.619	2247.401	260.7
dummy 13	-568.261	239.810	-0.091	-2.370	0.019	-1041.712	-94.810	236.7
dummy 14	189.861	254.969	0.030	0.745	0.458	-313.517	693.239	251.7
dummy 15	1334.301	278.953	0.214	4.783	0.000	783.572	1885.030	275.4
dummy 16	-471.321	229.285	-0.075	-2.056	0.041	-923.992	-18.650	226.3
dummy 17	234.966	254.929	0.038	0.922	0.358	-268.333	738.266	251.6
dummy 18	266.373	252.430	0.043	1.055	0.293	-231.993	764.738	249.2
dummy 19	2480.999	240.382	0.397	10.321	0.000	2006.420	2955.578	237.3
dummy 20	72.757	253.726	0.012	0.287	0.775	-428.168	573.682	250.5
dummy 21	190.192	256.332	0.030	0.742	0.459	-315.877	696.260	253.0
dummy 22	-35.990	225.849	-0.006	-0.159	0.874	-481.878	409.898	222.9
dummy 23	-72.086	221.309	-0.012	-0.326	0.745	-509.009	364.837	218.5

Table B-4. Statistical output (from SPSS) using per country bias (dummy 1-41), the lower and upper bound for B with 95% confidence interval and the total uncertainty in the regression analysis.

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.	95.0% confidence interval for B		The total uncertainty in the regression analysis
	B	Std. Error	Beta			Lower bound	Upper bound	
dummy 24	1578.019	263.163	0.253	5.996	0.000	1058.464	2097.573	259.8
dummy 25	-962.458	228.573	-0.154	-4.211	0.000	-1413.723	-511.194	225.6
dummy 26	1926.405	249.631	0.308	7.717	0.000	1433.565	2419.244	246.4
dummy 27	-445.474	236.280	-0.071	-1.885	0.061	-911.955	21.008	233.2
dummy 28	-74.269	250.660	-0.012	-0.296	0.767	-569.140	420.602	247.4
dummy 29	845.093	267.057	0.135	3.164	0.002	317.849	1372.337	263.6
dummy 30	1989.238	256.931	0.318	7.742	0.000	1481.986	2496.490	253.6
dummy 31	-22.849	245.800	-0.004	-0.093	0.926	-508.125	462.427	242.6
dummy 32	-8.984	224.413	-0.001	-0.040	0.968	-452.037	434.069	221.5
dummy 33	1249.747	225.508	0.200	5.542	0.000	804.533	1694.962	222.6
dummy 34	2222.078	246.407	0.356	9.018	0.000	1735.603	2708.553	243.2
dummy 35	280.385	253.479	0.045	1.106	0.270	-220.052	780.822	250.2
dummy 36	-264.055	240.405	-0.042	-1.098	0.274	-738.680	210.570	237.3
dummy 37	648.068	263.263	0.104	2.462	0.015	128.316	1167.819	259.9
dummy 38	504.275	243.204	0.081	2.073	0.040	24.124	984.426	240.1
dummy 39	696.749	262.011	0.112	2.659	0.009	179.467	1214.030	258.6
dummy 40	1493.856	229.019	0.239	6.523	0.000	1041.710	1946.002	226.1
dummy 41	1224.604	230.877	0.196	5.304	0.000	768.791	1680.418	227.9

5. Changing global cropping patterns to minimize blue water scarcity in the world's hotspots

Abstract

Feeding a growing population with global natural resource constraints becomes an increasingly challenging task. Changing spatial cropping patterns and international crop trade could contribute to sustain crop production and mitigate water scarcity. Previous studies on water saving through international food trade focussed either on comparing water productivities among food-trading countries or on analysing food trade in relation to national water endowments. Here, we consider, for the first time, how both differences in water productivities and water endowments can be considered to analyse comparative advantages of countries for different types of crop production. A linear optimization algorithm is used to find modifications in global cropping patterns that reduce blue water scarcity in the world's hotspots, under the constraint of current global production per crop and current cropland areas. The optimization considers national water and land endowments as well as water and land productivity per country per crop. The results are used to assess national comparative advantages and disadvantages for different crops. When allowing a maximum expansion of harvested area per crop per country of 10%, the blue water scarcity in the world's most water-scarce countries can be greatly reduced. In this case, we could achieve a reduction of the current blue water footprint of crop production in the world of 9% and a decrease of global total harvested area of 4%.

5.1. Introduction

Water scarcity poses a major societal and economic risk (WEF 2019) and threat to biodiversity and environmental sustainability (Vörösmarty et al. 2010). Population growth and climate change are expected to worsen the situation and impose more pressure on freshwater resources everywhere (Parry et al. 2004, Vörösmarty et al. 2000). Since water consumption already exceeds the maximum sustainable level in many parts of the world (Hoekstra et al. 2012) and population growth in water-scarce countries alone could enforce global international trade in staple crops to increase by a factor of 1.4 to18 towards 2050 (Chouchane et al. 2018) solutions are urgently needed for a more sustainable allocation of the world's limited freshwater resources (Hoekstra 2014, Konar et al. 2016).

Considerable debate has arisen over the last few decades on the pathways to overcome the problem of water scarcity and its implications (Gleick 2003), especially for agriculture, the largest consumer of freshwater, accounting for 92% of water consumption globally (Hoekstra and Mekonnen 2012). A growing number of studies addresses the question how to mitigate problems related to blue water scarcity (Kummu et al. 2016, Wada et al. 2014). Some proposed solutions focus on better water management in agriculture (Evans and Sadler 2008), for instance improving irrigation efficiency and precision irrigation (Greenwood et al. 2010, Sadler et al. 2005), better agricultural practices like mulching and drip irrigation (Chukalla et al. 2015, Mukherjee et al. 2010, Nouri et al. 2019), improved irrigation scheduling (Jones 2004) and enhancing water productivity (Bouman 2007, Molden et al. 2010, Pereira et al. 2012). Other suggested solutions focus on changing diets to reduce water consumption (Jalava et al. 2014, Vanham et al. 2013). Yet another category of studies focusses on spatial cropping patterns (Davis et al. 2017a) and the role of international trade in saving water and in bridging the gap between national water demand and supply in water-short countries (Chapagain et al. 2006, Hoekstra and Hung 2005). The trade in 'embedded water' through food trade is known as virtual water trade (Allan 1998). According to international trade theory, countries can profit from trade by focussing on the production and export of goods for which they have a comparative advantage. What precisely constitutes comparative advantage is still subject to debate. Whereas Ricardo's theory of comparative advantage says that a country can best focus on producing goods for which they have relatively high productivity, the Heckscher-Ohlin theory states that a country can best specialize in producing and exporting products that use production factors that are comparatively most abundant. When focussing on the role of water in trade, the first theory would consider relative water productivity (crop per drop), while the second theory would look at relative water abundance (Hoekstra 2013). Part of the literature on water saving through international food trade has focussed on comparing water productivities among food-trading countries (Chapagain et al. 2006, Yang et al. 2006), while other studies have concentrated on analysing food trade in relation to water endowments (Chouchane et al. 2018, Yang et al. 2003). In the current study, we consider, for the first time, how both differences in water productivities and water endowments can be considered to analyse comparative advantages of countries for different types of crop production. While doing so, we also consider differences between countries in land productivities (crop yields) and land endowments (available cropland areas).

Studies on spatial allocation of crop production, given differences in land and water productivity and endowments are sparse, particularly large-scale studies. In local or regional studies that study best crop choices given land and water constraints, the focus is generally to maximize food production or agricultural value, without the requirement of fulfilling overall crop demand. Osama et al. (2017), for example, employ a linear optimization model for some regions in Egypt to maximize the net annual return by changing the cropping pattern, given water and land constraints, and conclude that some crops are to be expanded while others are to be reduced. Another example of a regional study is Ye et al. (2018), who used a multi-objective optimization model, considering the trade-offs between economic benefits and environmental impact of water use when changing the cropping pattern in a case study for Beijing. In a study for the US, Davis et al. (2017b) investigated an alternative crop distribution that saves water and improves productivity while maintaining crop diversity, protein production and income. The only global study on changing cropping patterns in order to reduce water use, to our knowledge, is Davis et al. (2017a), who combine data on water use and productivity for 14 major crops and show that changing the distribution of these crops across the currently cultivated lands in the world could decrease blue water use by 12% and feed an additional 825 million people.

Although it has been widely acknowledged that the spatial water scarcity pattern in the world can be explained by where crops are grown and how much they are irrigated (Mekonnen and Hoekstra 2016, Wada et al. 2011), it has not yet been studied how differences between countries in water and land productivities and endowments can be used to derive comparative advantages of countries for specific crops, and how a change in the global cropping pattern can reduce water scarcity in the places that are most water-scarce. Here, we explore how we can stepwise minimize the highest national water scarcity in the world by changing cropping patterns and blue water allocation to crops. For this purpose, we develop and apply a linear programming optimization algorithm considering a number of constraints. First, rainfed and irrigated harvested areas in each country should not grow beyond their extent in the reference period 1996-2005. Second, the harvested area per country per crop can only expand by a limited rate (which will be varied). Third, global production of each crop must remain the same as in the reference period. The optimization takes into account both factor endowments (blue water availability, rainfed land availability and irrigated land availability) in each country and factor productivities (blue water productivity in irrigation, and land productivities in rainfed and irrigated lands) for each crop in each country.

5.2. Method and Data

We developed a linear optimization algorithm in MATLAB. In the optimization we allow the global cropping pattern to change, that is to grow crops in different countries than in the reference situation. In the optimization, the cropping areas by crop, country and production system are the independent variables, and the following constraints are considered. First, both total rainfed and total irrigated harvested area per country are not allowed to expand. Second, both crop-specific rainfed and irrigated harvested area per country are allowed to expand, but not beyond a factor α (whereby we stepwise increase α from 1.1 to 2.0 in a number of subsequent experiments). Third, global production of each crop should remain equal to the global production of the crop in the reference situation. For any cropping pattern, the water scarcity in each country is computed, and the country with the highest water scarcity identified. The objective of the optimization is to minimize this highest water scarcity. The algorithm allows blue water scarcity in water-abundant countries to increase, but continuously tries to reduce the blue water scarcity in the countries with the highest blue water scarcity. The algorithm will thus tend to reduce and equalize blue water scarcity in the most water-scarce countries.

Given the cropping pattern, production is computed per country and crop, both for rainfed and irrigated lands based on the harvested area and crop yields:

$$\forall i,j: P_{rf}(i,j) = A_{rf}(i,j) \times Y_{rf}(i,j) \qquad \text{(Eq. 5-1)}$$

$$\forall i,j: P_{ir}(i,j) = A_{ir}(i,j) \times Y_{ir}(i,j) \qquad \text{(Eq. 5-2)}$$

$$\forall i,j: P(i,j) = P_{rf}(i,j) + P_{ir}(i,j) \qquad \text{(Eq. 5-3)}$$

whereby $P_{rf}(i,j)$, $P_{ir}(i,j)$ and $P(i,j)$ are the rainfed, irrigated and total production in country i of crop j; $A_{rf}(i,j)$ and $A_{ir}(i,j)$ the rainfed and irrigated harvested area in country i for crop j; and $Y_{rf}(i,j)$ and $Y_{ir}(i,j)$ the rainfed and irrigated crop yield in country i for crop j.

Blue water scarcity (BWS) is defined per country i as the total blue water footprint divided by the blue water availability in the country (Hoekstra et al., 2012).

$$BWS(i) = \frac{\sum_j P_{ir}(i,j) \times BWF(i,j)}{BWA(i)} \qquad \text{(Eq. 5-4)}$$

where $P_{ir}(i,j)$ is the irrigated production in country i of crop j, $BWF(i,j)$ the blue water footprint per unit of crop j in country i, and $BWA(i)$ the blue water availability in country i. A country is considered to be under low, moderate, significant or severe water scarcity when BWS (expressed as a percentage) is lower than 20%, in the range 20-30%, in the range 30-40% and larger than 40%, respectively (Hoekstra et al., 2012).

The optimization can be presented as follows:

$$\min_{A_{rf},A_{irr}} \left(\max_i(\mathrm{BWS(i)})\right) \qquad \text{(Eq. 5-5)}$$

subject to:

$$\forall i: \sum_j A_{rf}(i,j) \leq \sum_j A_{rf,ref}(i,j) \quad \text{(Eq. 5-6)}$$

$$\forall i: \sum_j A_{ir}(i,j) \leq \sum_j A_{ir,ref}(i,j) \quad \text{(Eq. 5-7)}$$

$$\forall i,j: A_{rf}(i,j) \leq \alpha \times A_{rf,ref}(i,j) \quad \text{(Eq. 5-8)}$$

$$\forall i,j: A_{ir}(i,j) \leq \alpha \times A_{ir,ref}(i,j) \quad \text{(Eq. 5-9)}$$

$$\forall j: \sum_i P(i,j) = \sum_i P_{ref}(i,j) \quad \text{(Eq. 5-10)}$$

where $A_{rf}(i,j)$ and $A_{ir}(i,j)$ are the rainfed and irrigated harvested areas in country i of crop j in the cropping pattern that is varied in order to minimize the highest national blue water scarcity, $A_{rf,ref}(i,j)$ and $A_{ir,ref}(i,j)$ are the rainfed and irrigated harvested areas in the reference situation), $P(i,j)$ is the total (rainfed plus irrigated) production in country i of crop j in the new cropping pattern, and $P_{ref}(i,j)$ is the total (rainfed plus irrigated) production in country i of crop j in the reference situation. Parameter α is the factor of maximally allowed expansion of the harvested area per crop and country and production system (rainfed or irrigated), which is varied in the optimization experiments between 1.1 and 2. Note that total national croplands (both rainfed and irrigated) are not allowed to expand, but that reductions in land use are always allowed.

A country is considered to have a comparative advantage for producing a certain crop or crop group when the following criteria are met: (1) the relative change (production in the optimized cropping pattern divided by the production in the reference situation) of that crop or crop group continues to increase in that country when we gradually increase the maximum allowed expansion of harvested area per crop per country (the factor α); and (2) the share of the country in the global production of the crop or crop group exceeds 5% (in the optimized cropping pattern at $\alpha = 1.1$).

The sources of the data used to perform the optimization are summarized in Table 5-1.

Table 5-1. Overview of data used.

Variable	Spatial resolution	Temporal resolution	Source
Blue water availability	Country (internal + external renewable water resources)	Average for 1961-1990	FAO (2018)
Harvested irrigated and rainfed land per crop in the reference situation	Country	Average for 1996-2005	Mekonnen and Hoekstra (2011)
Rainfed and irrigated production per crop in the reference situation	Country	Average for 1996-2005	Mekonnen and Hoekstra (2011)
Blue WF per unit of crop in irrigated production per crop	Country	Average for 1996-2005	Mekonnen and Hoekstra (2011)
Yield in rainfed and irrigated production per crop	Country	Average for 1996-2005	Mekonnen and Hoekstra (2011)

5.3. Results

5.3.1. Changes in blue water scarcity and blue water consumption

When α is 1.1, that means when we allow a maximum of 10% expansion of the reference harvested areas for each individual crop, in every country, both for rainfed and irrigated production, blue water scarcity in the world's seven most water-scarce countries, Libya, Saudi Arabia, Kuwait, Yemen, Qatar, Egypt, and Israel (with current scarcities ranging from 54% to 270%) is reduced to a scarcity of 39% or less (Table 5-2). In this scenario, the aggregated blue water footprint of crop production in the world will get reduced by 9%, while the total global harvested area will be reduced by 4%.

When α is equal to 1.3, 1.5 and 2.0 (i.e., when the maximally allowed expansion of harvested area per crop per country is equal to 30%, 50% and 100%), the maximum national blue water scarcity in the world is reduced to 6%, 4% and 2%, respectively. In these scenarios, global blue water consumption gets reduced by 34, 47 and 58%, respectively, while the total global harvested area gets reduced by 6%, 7% and 9%, respectively.

Table 5-2. Current versus optimized blue water consumption (BWC) and blue water scarcity (BWS) for countries currently having a water scarcity higher than 15%.

Countries	Current		Optimized ($\alpha = 1.1$)		Optimized ($\alpha = 1.3$)		Optimized ($\alpha = 1.5$)		Optimized ($\alpha = 2.0$)	
	BWC (10^6 m^3/y)	BWS (%)	BWC (10^6 m^3/y)	BWS (%)	BWC (10^6 m^3/y)	BWS (%)	BWC (10^6 m^3/y)	BWS (%)	BWC (10^6 m^3/y)	BWS (%)
Libya	1900	270%	280	39%	41	6%	25	4%	16	2%
Saudi Arabia	6200	260%	940	39%	140	6%	86	4%	54	2%
Kuwait	48	240%	8	39%	1	6%	1	4%	0	2%
Yemen	2100	98%	3	0%	29	1%	75	4%	47	2%
Qatar	51	88%	23	39%	3	6%	2	4%	1	2%
Egypt	34000	57%	17000	30%	3400	6%	2100	4%	1300	2%
Israel	960	54%	54	3%	49	3%	64	4%	40	2%
Jordan	410	43%	0	0%	10	1%	34	4%	21	2%
Syria	7000	42%	2600	15%	990	6%	600	4%	380	2%
Oman	550	39%	520	37%	82	6%	50	4%	31	2%
Uzbekistan	15000	31%	13000	27%	2900	6%	1800	4%	1100	2%
Cyprus	240	31%	0	0%	2	0%	28	4%	17	2%
Pakistan	74000	30%	67000	27%	14000	6%	8900	4%	5500	2%
Iran	40000	29%	40000	30%	8000	6%	4900	4%	3100	2%
Tunisia	1300	29%	400	9%	270	6%	170	4%	100	2%
Algeria	2700	23%	1100	10%	690	6%	420	4%	260	2%
Turkmenistan	5300	21%	500	2%	1500	6%	890	4%	550	2%
Morocco	5100	18%	1500	5%	1700	6%	1000	4%	650	2%
Malta	9	17%	0	0%	0	0%	2	4%	1	2%
Lebanon	770	17%	45	1%	54	1%	160	4%	100	2%
Sudan	6100	16%	700	2%	2200	6%	1400	4%	850	2%
Global	**820000**		**750000**		**540000**		**440000**		**350000**	

Most countries with severe water scarcity (BWS>40%) in the reference situation will have a moderate (BWS in the range 20-30%) to low water scarcity (BWS<20%) in the optimized situation with α = 1.1 (Figure 5-1). The blue water scarcity reduction in most countries comes at the price of a slight increase in BWS of some countries. In India, BWS increases from 12.1 % to 12.7%, in Iran from 29.1 % to 29.6 % and in Turkey 7.2% to 7.4%.

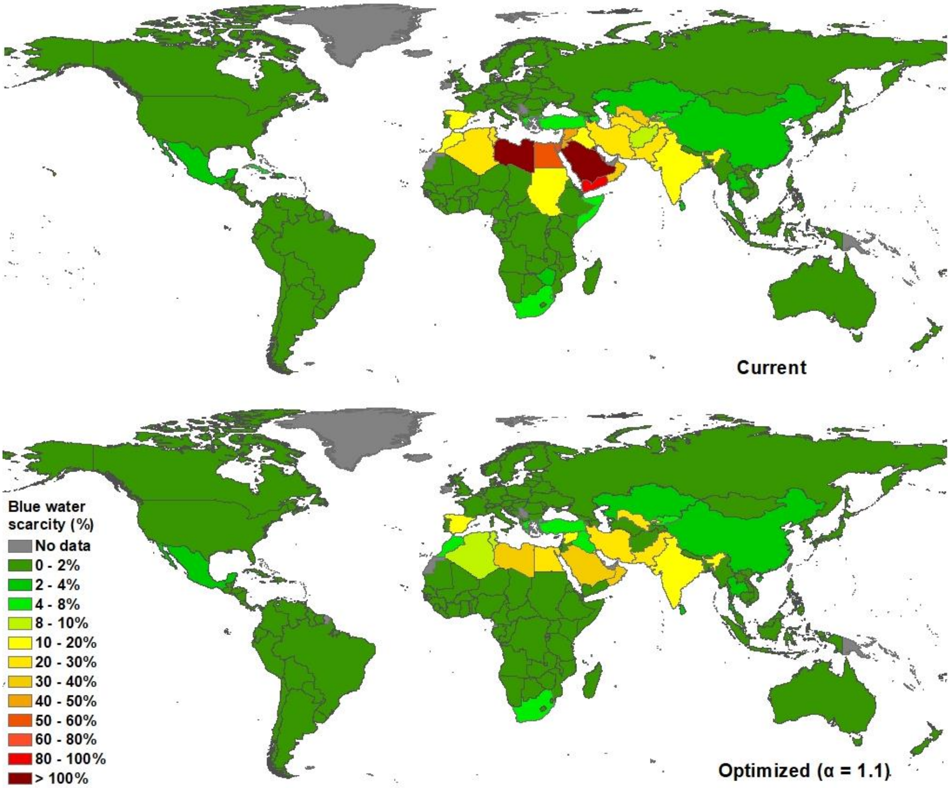


Figure 5-1. Current and optimized (α=1.1) blue water scarcity.

In the case of α = 1.1, Egypt will have the largest reduction in its blue water consumption in absolute terms, viz. 17,000 m^3/y, which represents 50% of its current BWC and 24% of the global blue water saving. Other countries that have a significant reduction in their BWC in absolute terms include Pakistan, Sudan, Saudi Arabia, Afghanistan, Turkmenistan, Iraq and Syria. Although the largest consumer of blue water in the reference situation, Pakistan, will get its current BWC reduced by 10%, the other two larger consumers, India and China, will have slight increases in their BWC (5% and 4% respectively) (Figure 5-2). Other countries that will have an increase in their BWC (e.g. Australia, Austria, Bangladesh, Congo, the Democratic Republic of the Congo, Greece, Japan, Malaysia, Norway, Turkey, Uruguay, and Sierra Leona) have a relatively low initial BWC.

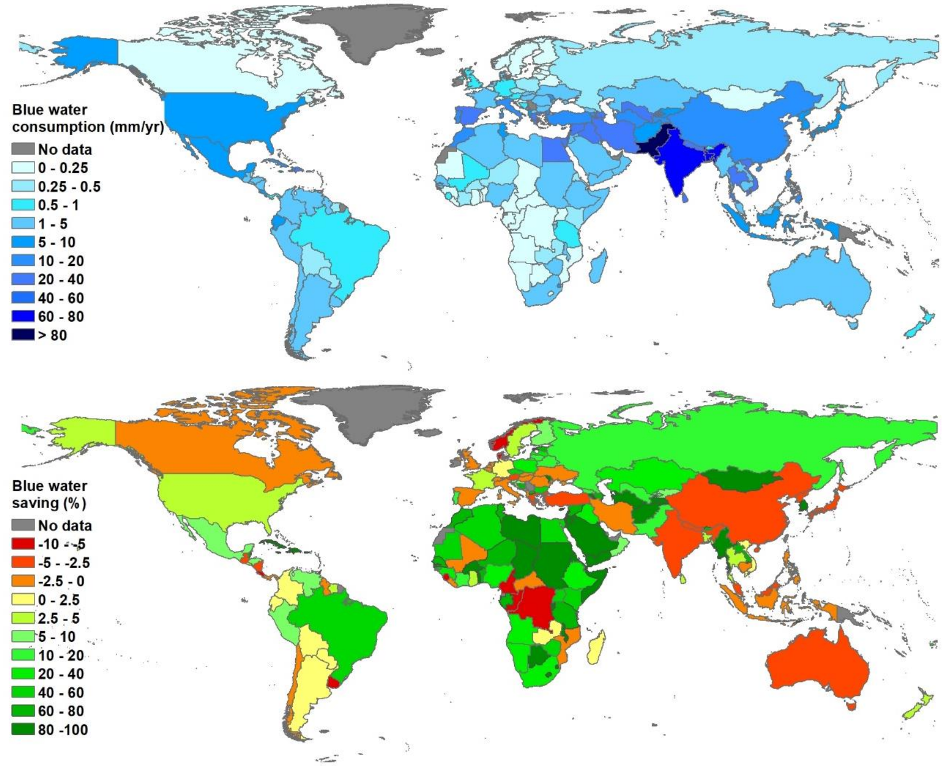


Figure 5-2. Current blue water consumption (BWC) in mm/y and blue water saving as a percentage of current BWC in the case of an optimized cropping pattern (α = 1.1).

5.3.2. The changing global cropping pattern for the case of α = 1.1

The reduction of global blue water consumption is achieved by reallocating crops from countries that initially have a high BWS to countries that have a lower BWS and higher productivity in terms of land and water. Cereal production will be reduced most significantly in Africa and the Americas and expanded in Europe and Asia (Table 5-3). Irrigated cereal production will be reduced in all world regions whereas global rainfed production increases. In Africa, Egypt will have the biggest percentage of total cereal production decrease. The harvested area of cereals in Africa will be reduced by 8 million hectares in total (Appendix Table C-1), which represents 9% of the current harvested area of cereals in Africa. The irrigated area of cereals in Africa will be reduced by 50% compared to the reference situation and the rainfed area by 5%. North America will have the largest increase in maize production, although the US will have the largest net reduction in overall cereal production due to a reduction in wheat and rice production. The irrigated and rainfed harvested areas of cereals in North America will be reduced by 21% and 7%, respectively. For South America, the most significant reductions in cereal production are related to rice production in Argentina and Brazil and wheat production in Brazil. The harvested area of cereals will be reduced by 14% in South America (the irrigated area will shrink by 29% and the rainfed area by 12%). The most significant expansions in cereal production are in France, Germany and China for wheat production and in India and China for rice production. Europe has the largest increase in rainfed cereal production. The harvested area will be expanded in total by 2% in Europe (-11% irrigated and +3% rainfed) and reduced by 1% in Asia (-2% irrigated and +1% rainfed). The global harvested area of cereals will be reduced by 3% in total compared to the reference situation. The irrigated area will be reduced by 6% and the rainfed area by 2%.

Fruit production will be reduced most significantly in Africa and Europe and expanded in the Americas (Table 5-3). Major fruit production reductions include the decrease of grape production in South Africa, banana production in Tanzania, orange production in Spain and apple production in the Russian Federation. In North America, the most significant expansion in fruit production is the increase in orange, grape and apple production in the US; in South America, the largest fruit production increases are oranges in Brazil and bananas in Ecuador. Although fruit production reduction in Africa, Asia and Europe is mainly irrigated, the irrigated production of fruits will increase in the Americas and Oceania. Half of the increase in irrigated production in North America comes from the increase in irrigated production of oranges, apples and grapes in the US. The world's harvested area of fruits will be reduced by 5%. The irrigated area will be reduced by 12% and the rainfed area by 2%.

The production of oil crops will be reduced most significantly in Africa (e.g. oil palm in Nigeria) and expanded in North America (e.g. soybeans in the US). The harvested area will shrink globally by 5% in total. Irrigated areas will be reduced by 17% and rainfed with 3%. Africa and Asia will have the most significant shrinkage in harvested areas of oil crops.

Roots production will partly move from Asia to Europe. The most significant reduction will be due to the decrease of potato production in India and cassava production in Thailand. The largest expansions are potato production in the Russian Federation, Poland, Ukraine and Germany. Globally, the harvested area of roots will be reduced by 5% (25% for irrigated and 3% for rainfed croplands).

Table 5-3. Change in production per product group per continent in absolute terms (10^6 t/y) when shifting from the cropping pattern in the reference period (1996-2005) to the optimized cropping pattern (with α=1.1).

		Cereal	Fibres	Fruits	Nuts	Oil crops	Pulses	Roots	Spices	Stimulants	Sugar crops	Vegetables
Africa	Rainfed	0.50	0.25	0.76	0.09	-8.41	0.29	2.74	-0.18	0.31	0.82	-1.23
	Irrigated	-14.68	-0.26	-7.14	-0.05	-0.98	-0.16	-2.43	-0.07	-0.06	-33.94	-2.82
	Total	**-14.17**	**-0.02**	**-6.38**	**0.05**	**-9.40**	**0.12**	**0.31**	**-0.25**	**0.25**	**-33.12**	**-4.05**
Asia	Rainfed	15.84	-1.30	8.68	0.06	1.68	0.11	4.23	0.27	-0.14	11.62	27.46
	Irrigated	-3.51	-0.36	-7.17	0.00	-4.35	-0.84	-15.32	-0.03	0.05	-4.12	-14.29
	Total	**12.32**	**-1.66**	**1.51**	**0.06**	**-2.67**	**-0.73**	**-11.09**	**0.25**	**-0.09**	**7.50**	**13.16**
Europe	Rainfed	17.54	-0.03	-2.90	-0.13	-1.68	-0.03	8.92	-0.02	0.00	-9.53	-9.74
	Irrigated	-1.07	0.16	-2.86	0.00	0.05	-0.38	-1.03	0.00	0.00	2.71	1.47
	Total	**16.47**	**0.13**	**-5.76**	**-0.13**	**-1.63**	**-0.41**	**7.90**	**-0.02**	**0.00**	**-6.82**	**-8.27**
North America	Rainfed	2.20	0.56	1.13	-0.01	8.53	0.58	-0.75	0.01	-0.05	5.44	-0.92
	Irrigated	-8.86	0.51	4.00	0.12	0.73	0.09	1.54	0.01	0.00	-13.46	0.95
	Total	**-6.67**	**1.07**	**5.13**	**0.11**	**9.26**	**0.67**	**0.79**	**0.02**	**-0.05**	**-8.02**	**0.03**
Oceania	Rainfed	1.30	0.00	0.05	0.00	-0.27	0.02	-0.06	0.00	0.00	-7.47	-0.11
	Irrigated	-0.42	0.15	0.17	0.00	0.00	0.00	0.12	0.00	0.00	2.89	0.11
	Total	**0.88**	**0.15**	**0.23**	**0.00**	**-0.27**	**0.02**	**0.06**	**0.00**	**0.00**	**-4.57**	**0.00**
South America	Rainfed	-5.36	0.31	4.86	-0.10	5.09	0.30	1.66	0.00	0.01	35.44	-1.17
	Irrigated	-3.47	0.02	0.41	0.01	-0.39	0.03	0.38	0.01	-0.12	9.61	0.30
	Total	**-8.84**	**0.33**	**5.27**	**-0.09**	**4.70**	**0.33**	**2.04**	**0.01**	**-0.11**	**45.04**	**-0.87**

Sugar crop production will be reduced most significantly in Africa and expanded in South America. Sugar cane production will be mainly reduced in Egypt and Sudan and expanded in Brazil. The global harvested area of sugar crops will be reduced in total by 3%.

Vegetable production will be reduced most significantly in Europe and expanded in Asia. Major reductions in vegetable production are for cabbages and tomatoes in the Ukraine. The most significant expansions are the increases in tomato and watermelon production in China. The global harvested area of vegetables will be reduced by 7%, with a reduction of 14% for irrigated and 5% for rainfed croplands.

Although rainfed harvested areas will be reduced in Africa and North America for example (Appendix Table C-1), rainfed cereal production in these two continents will increase by 0.5 and 2.2 million t/y, respectively. This illustrates that by allocating production to more productive countries we can reduce water and land use and increase production at the same time.

5.3.3. Comparative advantages

We explore comparative advantages of countries by considering which crops in a country are expanding when we gradually move from $\alpha = 1.1$ to $\alpha = 1.5$. As a summary, Figure 5-3 shows at the level of continents and crop groups, the ratio of change in total production when we move from the reference cropping pattern (period 1996-2005) to the optimized cropping pattern, considering a stepwise increase in the maximally allowed expansion rate in harvested area per crop per country (from $\alpha = 1.1$ to $\alpha = 1.5$). Most of the changes in production under an allowed 10% areal expansion (Table 5-3) will continue under larger expansion rates, with some exceptions. This is, for example, the case for fibres in Europe and oil crops in North America. Fibres production will expand for the case of α=1.1, 1.2 and 1.3 in Europe but will be reduced for higher expansion rates. This can be explained by the fact that other suitable regions, namely Oceania, North America and to a lesser extent Africa, will continue expanding fibres production, allowing Europe to rather focus on cereals, sugar crops and stimulants production (Figure 5-3). North America reduces cereal production when α=1.1 (Table 5-3) but increases cereal production when α=1.2 and will have the largest expansion in cereal production for α=1.5 (Appendix Table C-1). This can have two reasons. The first reason is that for the smallest expansion rate, North America still needs to produce oil crops, and the global production could not be reached without the expansion of oil crops in North America and thus limited harvested area can be allocated to cereals. The second reason is that, as mentioned previously, even at the lowest expansion rate, the US will have the largest increase in maize production. From α=1.2 the expansion of maize in the US will be larger than the reduction of other cereal crops in North America, which results in a positive net expansion of cereals. This example for North America shows that it is hard to have a robust conclusion on comparative advantages by looking at the level of continents. In order to explore comparative advantages, we will need to look at country level. Figure 5-4 shows the relative changes in production per crop group per country when we move from the cropping pattern in the reference situation to the optimized cropping pattern with α = 1.5. Figure 5-5 gives the production per crop group per country in absolute terms for both the reference cropping pattern and the optimized cropping pattern with α = 1.5.

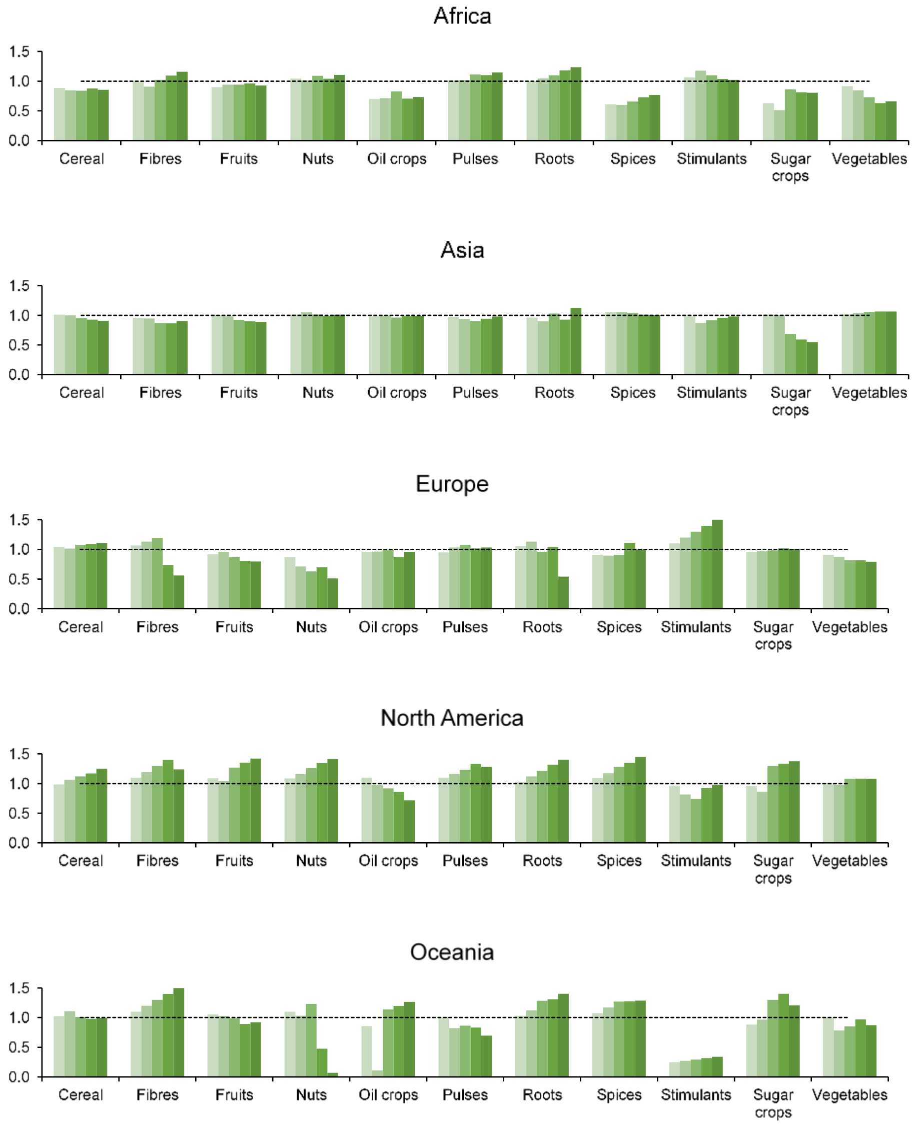


Figure 5-3. Ratio of total production in the optimized cropping pattern to total production in the reference cropping pattern (period 1996-2005), per crop group and per continent, for α = 1.1 to α = 1.5.

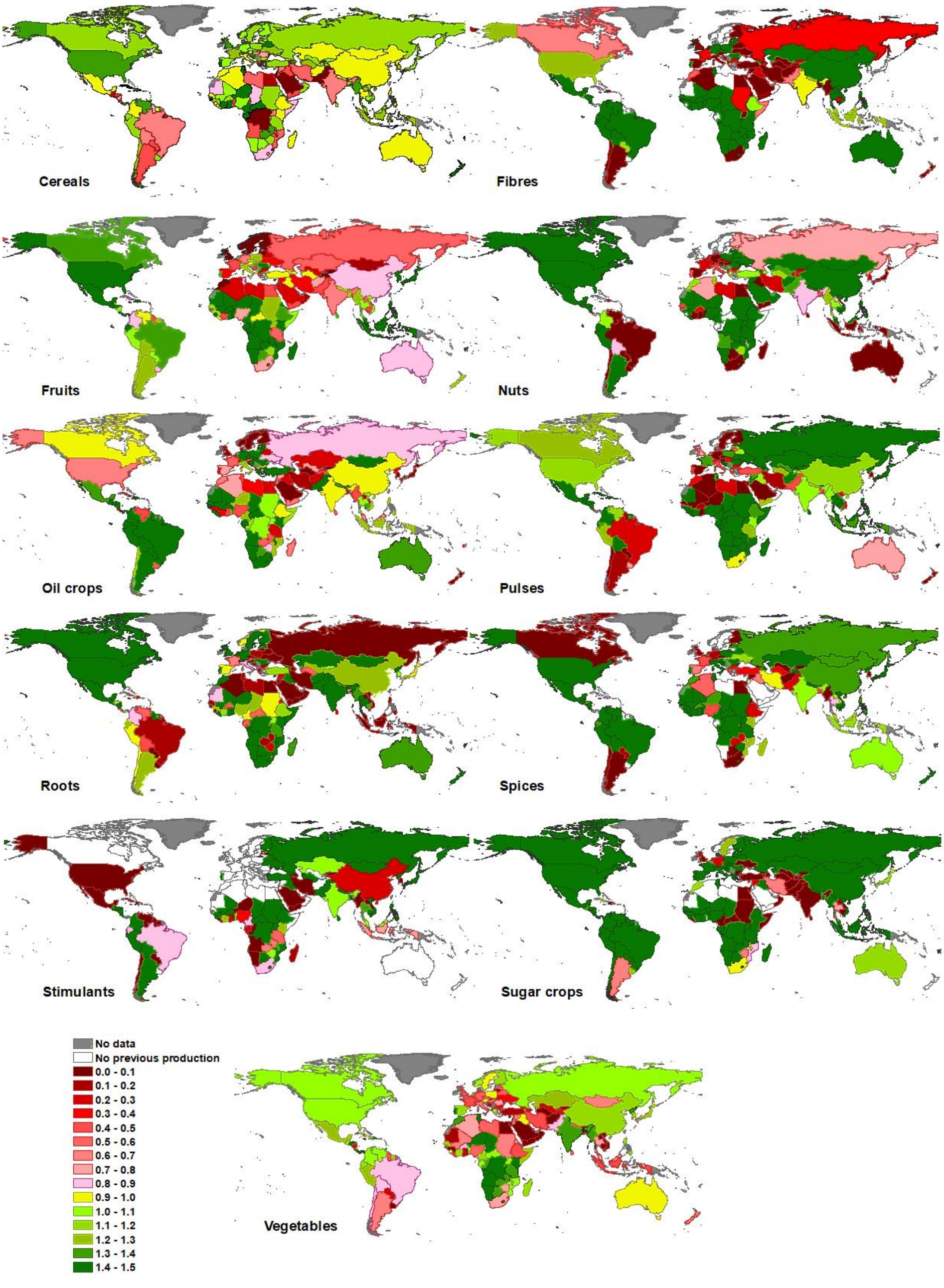


Figure 5-4. Relative change in production per country and per crop group for the case of an optimized cropping pattern with $\alpha = 1.5$.

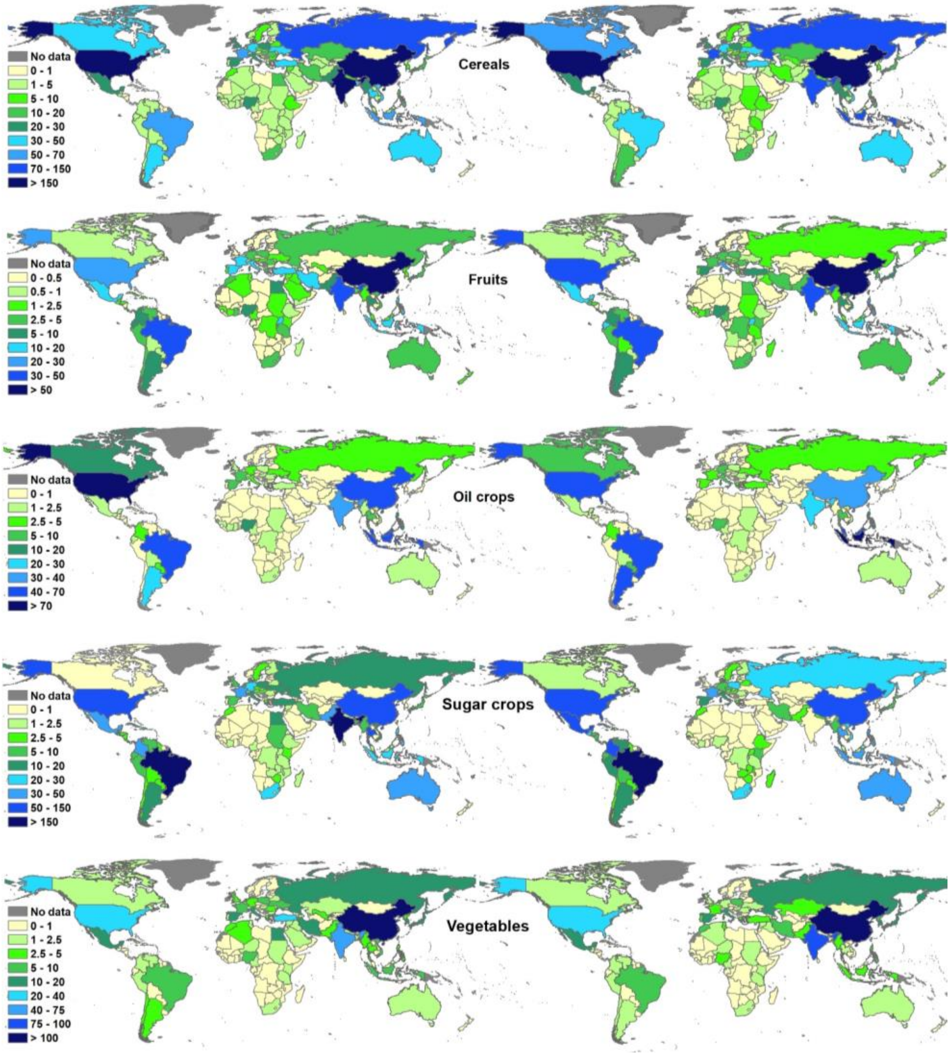


Figure 5-5. Production per crop group per country (in 10^6 t/y) in the reference situation (maps on the left hand) and in the case of an optimized cropping pattern with $\alpha = 1.5$ (maps on the right hand).

5.3.3.1. Cereal production

France and the US have both a large relative change (Figure 5-4) and absolute change (Figure 5-5) for cereals and thus a comparative advantage (given the combination of their water endowments and water productivities compared to other countries). In the case of $\alpha = 1.5$, cereal production of France and the US will increase by 23 and 30%, respectively, compared to the reference situation. India has a comparative disadvantage in cereals and will reduce its production by 40% in the optimized cropping pattern with

$\alpha = 1.5$. Looking at the main cereal crops separately (wheat, barley, maize and rice) and combining information on relative and absolute changes, we find that France and the Russian Federation have a comparative advantage in wheat production, with large absolute increases when we optimize the global cropping pattern (Appendix Figure C-1). India and China, contributing 12% and 17% respectively of global wheat production in the reference period, have a comparative disadvantage and shrink their wheat production by 46% for China and 27% for India when $\alpha = 1.5$. For barley, we find Canada, France, Spain, and Turkey to have a comparative advantage. Germany and the Russian Federation, contributing 9% and 11% respectively to the global barley production in the reference period, have a comparative disadvantage and will decrease their barley production respectively by 40% and 84% when $\alpha = 1.5$. For maize, the US is found to have a comparative advantage, while, Brazil, contributing 6% to global maize production in the reference period, has a comparative disadvantage and will reduce its maize production with 64% in the optimized situation ($\alpha = 1.5$). For rice, China, Indonesia and Vietnam have a comparative advantage, with shares in global rice production raising from 32%, 9% and 5% respectively in the reference situation to 40%, 11% and 9% in the optimised situation (when $\alpha = 1.5$). India, contributing 22% to global rice production in the reference period, has a comparative disadvantage and will decrease its rice production with 43% when $\alpha = 1.5$ compared to the reference situation.

5.3.3.2. Fruit production

Comparative advantages for fruit production are found for Brazil and the US, which will increase their respective shares in global fruit production from 7% and 6% in the reference situation to 10% and 9% in the optimized cropping pattern (when $\alpha = 1.5$). China and India, contributing 14% and 10% respectively to global fruit production in the reference period, appear to have a comparative disadvantage and will reduce their fruit production by 14% and 31% respectively in the optimized situation (when $\alpha = 1.5$). Zooming in to the top-4 produced fruits – apples, bananas, grapes and oranges – we find the following. For apples, the US has a comparative advantage; the country will increase its share in global apple production from 8% (reference) to 12% (when $\alpha = 1.5$). China, contributing 35% to the global apple production in the reference period, has a comparative disadvantage. Apple production in China will decrease by 16% in the optimized cropping patterns (when $\alpha = 1.5$). For bananas, Ecuador, Indonesia and the Philippines have a comparative advantage. Brazil and India, contributing 9% and 22% respectively to global banana production in the reference, have a comparative disadvantage. For grapes, China, Italy and the US have a comparative advantage, with shares in global grape production rising from 7%, 15% and 9% (reference) to 10%, 22% and 13% ($\alpha = 1.5$). France and Spain, contributing 13% and 9% respectively to the global grapes production in the reference situation, have a comparative disadvantage and will entirely abandon grapes production when $\alpha = 1.5$. For oranges, Brazil and the US have a comparative advantage, while Spain and Iran have a comparative disadvantage (Appendix Figure C-2).

5.3.3.3. Oil crops

For oil crops, we find Argentina and Brazil to have a comparative advantage. Their shares in global oil crops production will raise from 6% and 9% respectively (reference) to 9% and 13% ($\alpha = 1.5$). China, Malaysia and the US, contributing 9%, 12% and 17% respectively to global oil crops production in the reference situation, have a comparative disadvantage and will reduce their oil crops production by 10%, 21% and 33% respectively in the optimized cropping pattern (when $\alpha = 1.5$). Focussing on soybean, which contributes 36% to the global oil crops production, we find the comparative advantage for Argentina and Brazil. The share of Argentina and Brazil in global soybeans production will rise from 14% and 22% respectively (reference) to 21 and 33% ($\alpha = 1.5$). China and the US have a comparative disadvantage in soybeans production. While the US, contributing 43% to the global soybean production in the reference period, will reduce its production by 30%, China, contributing 9% in the reference period, will entirely stop its soybean production in the optimized pattern (when $\alpha = 1.5$) (Appendix Figure C-3).

5.3.3.4. Sugar crops

Brazil and China have a comparative advantage in sugar crops production, with shares in global sugar crops production rising from 23% and 6% respectively (reference) to 35% and 9% (optimized cropping pattern with $\alpha = 1.5$). India, currently contributing 18% to the global sugar crops production, has a comparative disadvantage and will quit sugar crops production almost entirely. Considering sugar beet and sugar cane separately, we find that France, Poland, the Russian Federation and the US have a comparative advantage in sugar beet production. Germany, Turkey and the Ukraine, contributing 11%, 7% and 6% to the global sugar beet production (reference), have a comparative disadvantage and will decrease their sugar beet production by 77%, 100% and 94% respectively (when $\alpha = 1.5$). For sugar cane, Brazil and China have a comparative advantage; their shares in global sugar cane production will increase from 28% and 6% respectively (reference) to 42% and 10% (optimized cropping pattern with $\alpha = 1.5$). India, contributing 22% to global sugar cane production in the reference period, has a comparative disadvantage and will decrease its sugar cane production by almost 100% (Appendix Figure C-3).

5.3.3.5. Vegetables

China and India have a comparative advantage in vegetable production. Their shares in global vegetable production will rise from 45% and 9% respectively (reference) to 52 and 12% respectively (optimized cropping pattern with $\alpha = 1.5$). Turkey, contributing 4% to global vegetable production in the reference, has a comparative disadvantage and will reduce its vegetable production by 88% in the optimized pattern (when $\alpha = 1.5$) compared to the reference situation. Looking at the most produced vegetable crop, tomato, which contributes 15% to global vegetable production, we find that China and the US have a comparative advantage (Appendix Figure C-3). The share of China and the US in the global production of tomatoes will increase from 21% and 11% respectively (reference) to 32% and 16% respectively (when $\alpha = 1.5$). Egypt and Turkey, contributing 6% and 8% to global tomatoes production in the reference, have a comparative disadvantage and will stop their production entirely in the optimized situation.

5.4. Discussion

One of the limitations of this study lies in the spatial resolution used in the analysis. Limited by data and our optimization model capability, we analyse the global cropping pattern at the country scale rather than at sub-national or grid scale. However, having a high average yield for a specific crop in a certain country doesn't necessarily mean that everywhere in that country the same performance in terms of land and water productivity will be achieved, due to spatial differences in crop suitability. This could mislead the optimization to reallocating crops to countries that have a very limited suitable production area but are productive in terms of water and land in the reference situation. To constrain this effect, we limit the expansion in cropland by a certain maximum rate for each crop per country (the factor α) and limit total cropland to the reference extent. The analysis at country level also has implications for measuring water scarcity. Assessing water scarcity at country level hides the water scarcity that manifests itself in particular places within countries (Mekonnen and Hoekstra 2016). We minimize *average* water scarcity in countries; within countries there will still be differences, not only in the reference but also in case of the optimized cropping patterns.

Another limitation of this study is the focus on water and land endowments and productivities, while other production factors such as labour, knowledge, technology and capital can be limiting factors to expand production of certain crops in some countries and certainly play a role in determining comparative advantages as well. Other factors could be included in a future study by refining the optimization model. Moreover, agricultural, trade and food security policies could be other factors that drive cropping patterns rather than water and land availability (Davis et al. 2018). Here, we purposely limited our analysis to considering comparative advantages from a land and water perspective to understand the specific role of these two particular factors. By no means we suggest that the 'optimized cropping patterns' found here are 'better' than the reference pattern because what is best depends on a lot more factors than included here, including political preferences. Rather, our results are instrumental in illustrating directions of change if we would put emphasis on the factors land and water endowment and productivity and put particular value to reducing water scarcity in the most water-scarce places.

The scope of the current study is restricted to the exploration of alternative cropping patterns to reduce water scarcity in the reference situation; we therefore use reference resource efficiencies. We do not take into consideration the future increase in food demand due to population growth, nor of climate change or agronomic developments that will affect the future ability of countries to produce crops.

The results suggest that Europe, for example, could contribute to global water scarcity mitigation by reducing its production of fruits, sugar crops and vegetables while increasing its cereal production. This implies that Europe will move to economically less attractive crops such as cereals. This illustrates the possible trade-off between the goal of reducing water scarcity in the most water-scarce countries and the goal of economic profit by producing cash crops by individual countries or regions. The optimization results do not pretend that the changes in production patterns are likely to occur, but merely that these changes reduce water scarcity most; national and international policies would be required to promote such water-saving changes to be implemented (Klasen et al. 2016).

For some countries, results show that the blue water footprint of crop production will be reduced by almost 100%: Antigua and Barbuda, Armenia, Barbados, Brunei Darussalam, Burkina Faso, Burundi, Cape Verde, Comoros, Cyprus, Djibouti, Dominican Republic, Eritrea, Gambia, Haiti, Jamaica, Jordan, Lesotho, Malawi, Malta, Mauritius, Moldova, Puerto Rico, Somalia, Swaziland, Timor-Leste, Togo and Trinidad and Tobago. This means that these countries will rely almost entirely on rainfed agriculture insofar possible and imports and thus be highly dependent on other countries. Most of these countries already have a high dependency on crop import in the reference situation. This reflects a trade-off between reducing water scarcity and increasing food security.

5.5. Conclusion

When allowing a 10% maximum expansion of harvested area per crop and per country, while not allowing an increase in total cropland per country, a global blue water saving in the world of 70,000 million m^3/y is achievable, which is 9% of the current global blue water footprint. Hereby, the total global harvested area would decrease by 4%. The blue water scarcity in the world's seven most water-scarce countries, Libya, Saudi Arabia, Kuwait, Yemen, Qatar, Egypt, and Israel (with current scarcities ranging from 54% to 270%), can be reduced to a scarcity of 39% or less. Optimizing the global cropping pattern to reduce the highest national water scarcity comes along with trade-offs, whereby severely water-scarce countries will reduce water scarcity at the expense of increased import-dependency.

When considering how to change the global cropping pattern in order to reduce water scarcity in the world's water-scarcity hotspots, we particularly find the following major shifts. Cereal production will get reduced in Africa and the Americas and increased in Europe and Asia. Fruits production will be reduced most significantly in Africa and Europe and expanded in the Americas. Oil crops production will be reduced most significantly in Africa (e.g. oil palm in Nigeria) and expanded in North America (e.g. soybeans in the US). Sugar crop production will be reduced most significantly in Africa and expanded in South America. Sugar cane production will be mainly reduced in Egypt and Sudan and expanded in Brazil. Vegetable production will be reduced most significantly in Europe and expanded in Asia. The most significant expansion in vegetable production will be an increase in tomatoes and watermelons in China.

From and water and land perspective, comparative advantages for cereal production are found for France and the US, whereas India has a comparative disadvantage. The comparative advantage of France refers to wheat and barley, and the comparative advantage of the US to maize. India's comparative disadvantage in cereal production particularly refers to wheat and rice. For fruit production, Brazil and the US are found to have a comparative advantage, whereas China and India have a comparative disadvantage. More in particular, the US has a comparative advantage for apples, grapes and oranges, and Brazil for oranges, while China has a comparative disadvantage in apples, and India for bananas. For oil crops, Argentina and Brazil have a comparative advantage, and China, Malaysia and the US a comparative disadvantage. Brazil and China have a comparative advantage for sugar cane, while India has a comparative disadvantage for sugar cane. For vegetables, we find China and India to have a comparative advantage and Turkey to have a comparative disadvantage. China has a comparative advantage for tomatoes and Turkey a comparative disadvantage.

By considering differences in national water and land endowments, following the Heckscher-Ohlin (H-O) theory of comparative advantage, as well as differences in national water and land productivities, following Ricardo's theory of comparative advantage, we combine two rationales that are both relevant. With the optimization exercises carried out in this study we show that blue water scarcity can be reduced to reasonable levels throughout the world by changing the global cropping pattern, while maintaining current levels of global production and reducing land use.

Appendix C

Table C-1. Change in harvested area per product group per continent in absolute terms (10^6 ha) when shifting from the cropping pattern in the reference period (1996-2005) to the optimised cropping pattern ($\alpha = 1.1$).

		Cereal	Fibres	Fruits	Nuts	Oil crops	Pulses	Roots	Spices	Stimulants	Sugar crops	Vegetables
Africa	Rainfed	-4.78	-0.04	-0.48	0.11	-4.82	-1.46	-1.43	-0.42	0.45	-0.17	-0.65
	Irrigated	-3.26	-0.24	-0.67	-0.06	-0.75	-0.08	-0.19	-0.04	-0.04	-0.34	-0.31
	Total	**-8.04**	**-0.27**	**-1.16**	**0.05**	**-5.57**	**-1.54**	**-1.62**	**-0.46**	**0.41**	**-0.51**	**-0.96**
Asia	Rainfed	0.75	-3.23	0.52	-0.41	-5.96	-2.45	-0.26	0.13	-0.59	0.22	0.52
	Irrigated	-3.54	-0.16	-0.83	-0.03	-2.48	-1.00	-0.93	-0.09	0.01	-0.22	-1.19
	Total	**-2.79**	**-3.39**	**-0.31**	**-0.44**	**-8.44**	**-3.45**	**-1.20**	**0.03**	**-0.58**	**0.00**	**-0.68**
Europe	Rainfed	3.71	-0.02	-1.16	-0.27	-1.13	-0.08	0.61	-0.03	0.00	-0.52	-1.11
	Irrigated	-0.79	0.05	-0.25	0.00	0.02	-0.07	-0.05	0.00	0.00	0.04	-0.06
	Total	**2.91**	**0.03**	**-1.40**	**-0.27**	**-1.10**	**-0.14**	**0.56**	**-0.03**	**0.00**	**-0.48**	**-1.18**
North America	Rainfed	-5.50	0.31	0.08	-0.01	3.58	0.45	-0.24	0.01	-0.23	0.13	-0.13
	Irrigated	-2.63	0.21	0.20	0.04	0.19	0.06	-0.01	0.00	0.00	-0.42	0.01
	Total	**-8.13**	**0.52**	**0.28**	**0.03**	**3.77**	**0.50**	**-0.25**	**0.01**	**-0.23**	**-0.29**	**-0.13**
Oceania	Rainfed	0.47	0.00	0.00	0.00	-0.21	-0.02	-0.01	0.00	0.00	-0.20	-0.02
	Irrigated	-0.11	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00
	Total	**0.36**	**0.04**	**0.01**	**0.00**	**-0.21**	**-0.02**	**-0.01**	**0.00**	**0.00**	**-0.18**	**-0.02**
South America	Rainfed	-3.74	0.17	0.30	-0.51	2.82	0.38	-0.06	0.00	-0.50	0.53	-0.18
	Irrigated	-1.10	0.01	-0.03	0.01	-0.11	0.01	0.01	0.00	-0.12	0.10	-0.04
	Total	**-4.83**	**0.18**	**0.28**	**-0.50**	**2.71**	**0.39**	**-0.05**	**0.00**	**-0.61**	**0.63**	**-0.21**

Table C-2. Change in production per product group per continent in absolute terms (10^6 t/y) when shifting from the cropping pattern in the reference period (1996-2005) to the optimised cropping pattern ($\alpha = 1.5$).

		Cereal	Fibres	Fruits	Nuts	Oil crops	Pulses	Roots	Spices	Stimulants	Sugar crops	Vegetables
Africa	Rainfed	0.4	1.7	6.0	0.2	-7.0	1.8	43.6	-0.1	0.1	11.3	-3.3
	Irrigated	-18.3	-0.9	-10.6	-0.1	-1.4	-0.5	-3.2	-0.1	0.0	-28.9	-13.2
	Total	**-17.9**	**0.8**	**-4.5**	**0.1**	**-8.3**	**1.4**	**40.4**	**-0.2**	**0.1**	**-17.6**	**-16.5**
Asia	Rainfed	15.3	5.8	29.9	0.7	8.2	-0.9	22.3	0.8	0.4	57.7	59.3
	Irrigated	-110.6	-9.7	-53.1	-0.6	-10.1	0.4	13.6	-0.8	-0.5	-326.2	-25.6
	Total	**-95.3**	**-3.8**	**-23.2**	**0.0**	**-1.9**	**-0.5**	**35.9**	**0.0**	**-0.1**	**-268.5**	**33.7**
Europe	Rainfed	48.4	-0.2	-8.1	-0.4	0.0	0.0	-72.3	0.0	0.0	-9.9	-19.8
	Irrigated	-6.7	-0.6	-6.5	-0.1	-1.5	0.3	9.0	0.0	0.0	11.0	1.1
	Total	**41.7**	**-0.8**	**-14.6**	**-0.5**	**-1.5**	**0.3**	**-63.2**	**0.0**	**0.0**	**1.1**	**-18.7**
North America	Rainfed	88.0	2.1	4.3	0.0	-18.6	1.6	2.6	0.0	0.0	41.5	-2.7
	Irrigated	18.7	0.5	20.0	0.5	-8.2	0.4	10.0	0.0	0.0	26.8	6.8
	Total	**106.7**	**2.6**	**24.3**	**0.5**	**-26.8**	**2.0**	**12.6**	**0.1**	**0.0**	**68.3**	**4.1**
Oceania	Rainfed	0.6	0.0	0.2	0.0	0.6	-0.7	0.1	0.0	0.0	-7.8	-0.6
	Irrigated	-0.8	0.7	-0.5	0.0	0.0	0.0	0.6	0.0	0.0	16.1	0.2
	Total	**-0.3**	**0.7**	**-0.3**	**0.0**	**0.6**	**-0.7**	**0.7**	**0.0**	**0.0**	**8.3**	**-0.4**
South America	Rainfed	-35.6	0.5	12.8	-0.1	37.6	-2.5	-29.0	0.0	0.1	160.5	-2.2
	Irrigated	0.7	0.1	5.5	-0.1	0.3	0.1	2.5	0.0	-0.1	48.0	0.0
	Total	**-34.9**	**0.6**	**18.4**	**-0.2**	**37.9**	**-2.4**	**-26.5**	**0.1**	**0.0**	**208.5**	**-2.2**

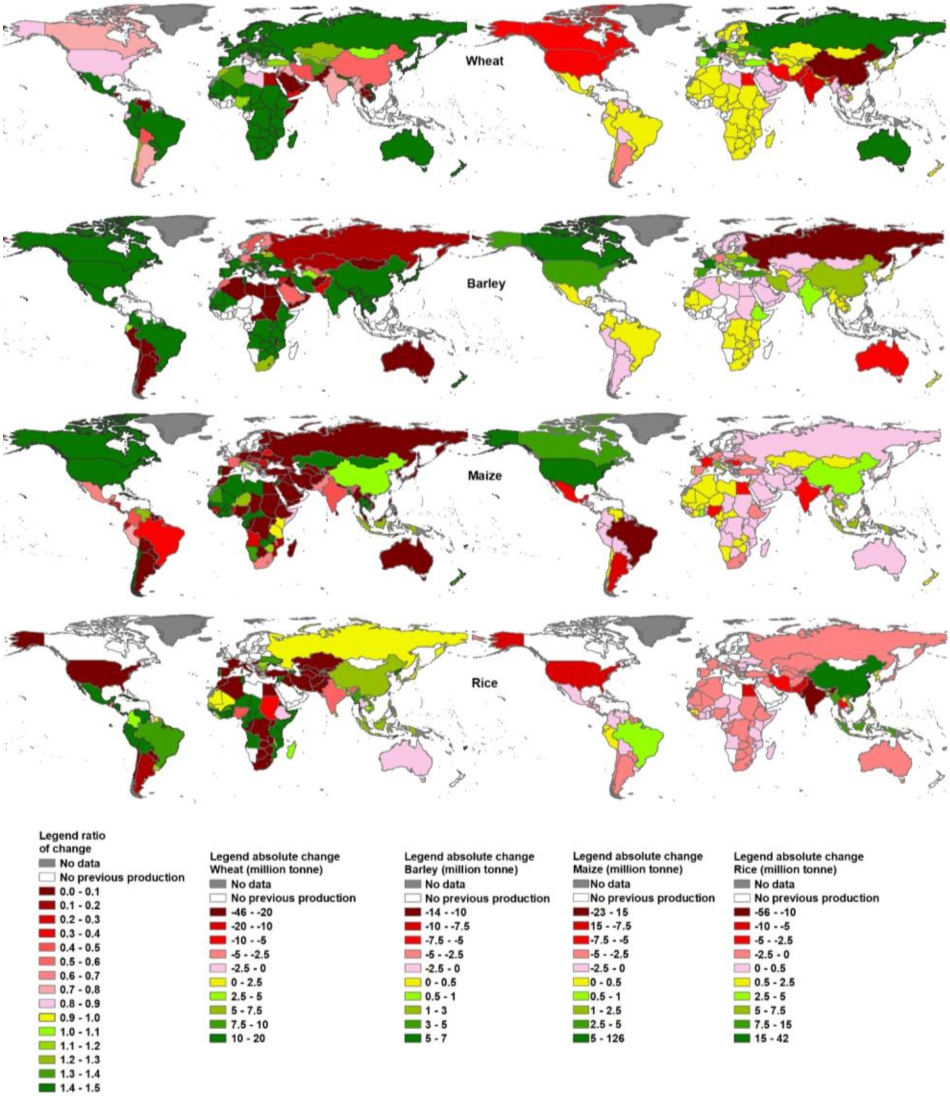


Figure C-1. Relative change in production for wheat, barley, maize and rice per country for the case of an optimized cropping pattern with $\alpha = 1.5$ (maps on the left hand) and absolute change (in 10^6 t/y) for the same crops (maps on the right hand), all compared to the reference cropping period (period 1996-2005).

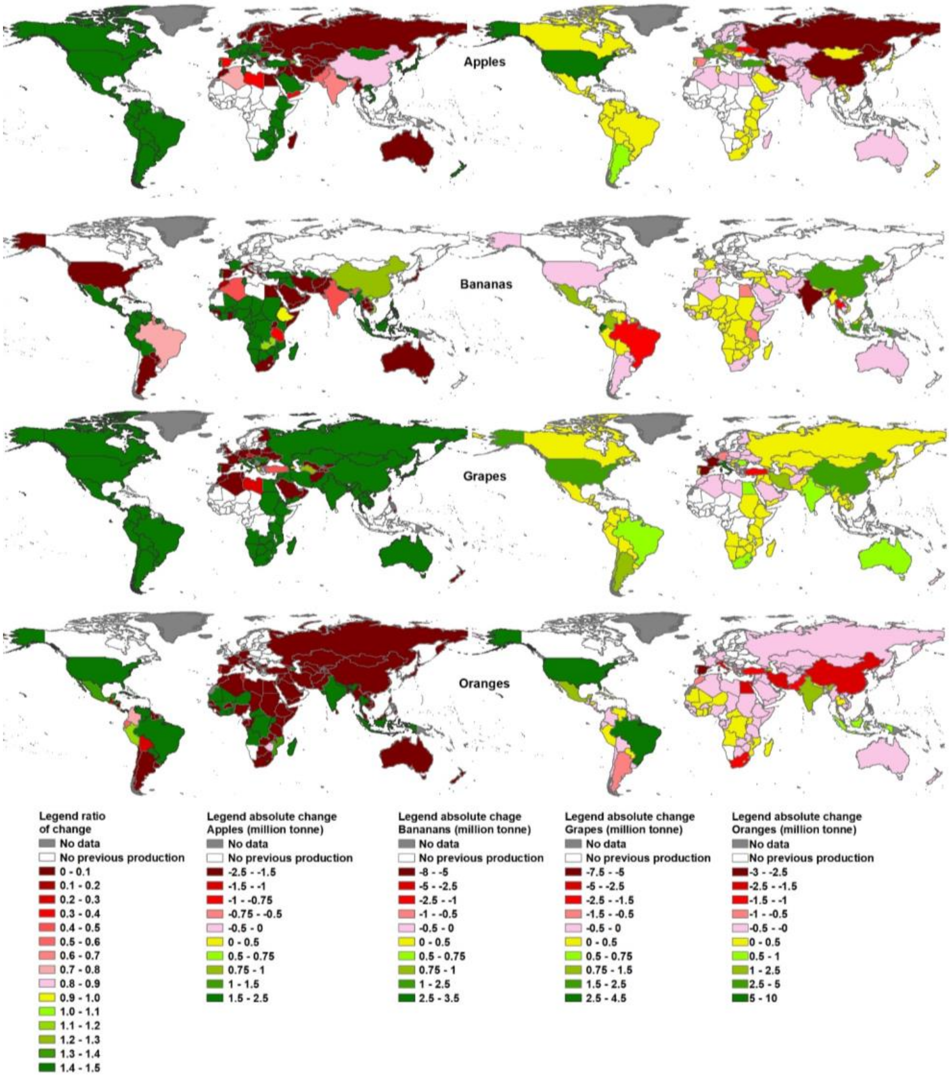


Figure C-2. Relative change in production for apples, bananas, grapes and oranges per country for the case of an optimized cropping pattern with $\alpha = 1.5$ (maps on the left hand) and absolute change (in 10^6 t/y) for the same crops (maps on the right hand), all compared to the reference cropping period (period 1996-2005).

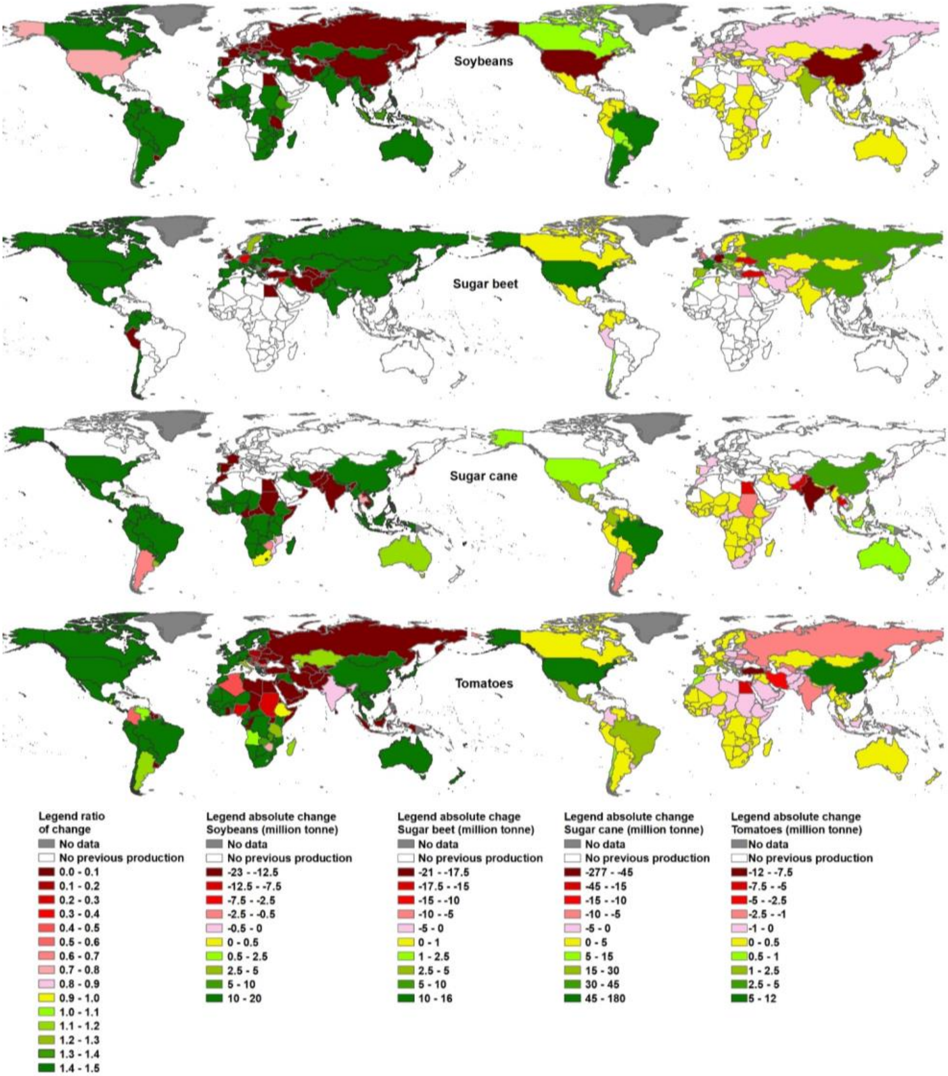


Figure C-3. Relative change in production for soybeans, sugar beet, sugar cane and tomatoes per country for the case of an optimized cropping pattern with $\alpha = 1.5$ (maps on the left hand) and absolute change (in 10^6 t/y) for the same crops (maps on the right hand), all compared to the reference cropping period (period 1996-2005).

6. Conclusion

The objective of this research was to investigate the economic efficiency of water and land allocation in crop production, the possible pathways to improve crop allocation considering comparative advantage and to explore the relationship between water scarcity and crop trade

6.1. Refection on research findings and contributions to scientific advancement

The study of water and land allocation of the main produced crops in a water-scarce country has revealed that even though Tunisia suffers from significant water scarcity, the biggest share of the country's blue WF (91%) is allocated to crops with relatively low economic water and land productivity: wheat, olives and dates (Chapter 2). The inefficient allocation of water and land is partly due to the agricultural policy followed by Tunisia which is mostly towards ensuring food self-sufficiency, which explains the water allocation to wheat production. Tunisian authorities encourage staple crop production which represents the largest share of the Tunisian diet. Olives and dates are the most exported crops, even though their economic water productivity is found to be relatively low. Beside the inefficient allocation of water and land given economic water and land productivities of different crops, the blue WF of most of the studied crops, except tomatoes, exceeds the global average. It may be profitable for Tunisian authorities to re-think their agricultural and trade policies to better adapt to the country's water scarcity situation and stimulate farmers to shift to crops with high economic water and land productivity and with lower blue WF and increase the import of staple crops. In terms of water and land productivity, oranges, potatoes and tomatoes are the most attractive crops among the main produced crops in Tunisia. For South Tunisia it is especially attractive to grow dates because the climate and growing conditions are very suitable for this crop; dates are not grown in North and Central. The ELP for dates was high as well, but the EWP was not. Furthermore, dates are mainly destinated for export which makes the economic return of water used in their production higher than being offered in the local market. The findings on water and land allocation at the national level are broadly consistent with the findings of Schyns and Hoekstra (2014) for Morocco and Garrido et al. (2010) for Spain.

Having the results of Chapter 2 in mind and knowing that a water-scarce country could benefit from trade by importing water-intensive products instead of producing them locally, one may think that there is a correlation between virtual water import of a water-scarce country and its blue water scarcity. However, studying the relation between

Tunisia's virtual water trade pattern over time in relation to environmental and socioeconomic factors, I found that blue water scarcity was not a significant influencing factor in explaining net virtual water import (NVWI) of selected crops in Tunisia during the period of study (Chapter 3). Other factors, mainly population, precipitation, irrigated area and GDP could better explain trends and annual variability of NVWI of staple crops (wheat, barley, potatoes) and less or not at all in explaining NVWI of cash crops (dates, olives, tomatoes). The finding that GDP, population and irrigated land are significant in explaining NVWI dynamics supports the results of Tamea et al. (2014), who studied the drivers of virtual water trade using gravity laws. The finding that blue water scarcity was not an influencing factor of virtual water trade in a water-scarce country is similar to the finding of Kumar and Singh (2005) and Fracasso et al. (2016), who found that water endowment and water scarcity were not driving factors for virtual water trade for specific countries. However, blue water scarcity may have indirectly influenced the temporal development of the irrigated area that was identified as a significant factor to explain net virtual water import for some crops.

To further investigate the relationship between trade and water availability, I considered the 42 most water-scarce countries of the world over a prolonged period (1961-2010) and studied the correlation between the net import of staple crops and per capita water availability (Chapter 4). The relationship found has been used to predict future imports considering projected population growth scenarios. The study results reveal that food import is partly influenced by water scarcity patterns. We found a statistically significant logarithmic shaped relation between net staple-food import in kcal/day per capita and blue water availability per capita. Most of the water-scarce countries follow the regression curve shape, with an exception of a few anomalously-behaving countries such as India, Pakistan and Sri Lanka. The curve found here has a similar shape as the relation found earlier by Yang et al. (2003), although they considered different countries, less staple crops and a shorter period of change, and looked at kg of import rather than kcal. As a result of population growth in water-scarce countries alone, global international trade in staple crops is projected to increase by a factor of 1.4 - 1.8 towards 2050 (compared to the average in 2001 - 2010), in order to meet the staple food needs of the 42 most water-scarce countries in the world. The finding of this study raises a number of challenges for future decades such as where additional amounts of staple crops in the future could be sourced from, and what additional water and other environmental impacts that may have in these other countries.

To examine crop allocation efficiency at the global level, a linear optimization algorithm was developed in order to find the cropping patterns that most reduce blue water scarcity in the world's hotspots, not allowing for cropland expansions while meeting the same global production for each crop (Chapter 5). The optimization looks at water and land endowments and water and land productivities per country per crop. Comparative advantages and disadvantages were estimated based on the optimization results. Results reveal that current cropping patterns are inefficient in avoiding water scarcity and could be improved. When allowing for an areal expansion of no more than 10% per crop per country while not expanding the overall rainfed and irrigated areas per country, global blue water consumption can be reduced by 9%. The blue water scarcity in the world's seven most water-scarce countries, Libya, Saudi Arabia, Kuwait, Yemen, Qatar, Egypt, and Israel (with current scarcities ranging from 54% to 270%) is reduced to a scarcity of 39% or less. In the new cropping patterns, cereal production will be reduced in Africa and the Americas and increased in Asia and Europe, fruit production will be increased in the Americas and reduced in Africa and Europe, oil crops production will be reduced in Africa and increased in North America, sugar crops production will be reduced in Africa and increased in South America and vegetable production will be reduced in Europe and increased in Asia. Most studies of comparative advantage focus on maximizing profit from the use of natural resources. However, our study focus was to minimize water scarcity by changing cropping patterns. The comparative advantage of this study is different from Ricardo's and H-O's comparative advantage. It combines both factors endowment and productivity in order to reduce water scarcity. It shows how collaboratively countries could save water and reduce scarcity. The findings on water allocation on a global level proves that if the comparative advantage is used to allocate water in every country, water scarcity can be reduced everywhere, but particularly in the most water-scarce countries. Our results support the finding of Davis et al. (2017) who studied the potential of water use reduction through changing cropping patterns and found that redistributing the major 14 crops can reduce blue water use by 12%.

The thesis contributes to the research field of water footprint assessment and virtual water trade studies in several ways. First, the work contributes by taking the economic perspective of water and land allocation together within a WF assessment, while earlier WF studies focus on water alone and stick to a physical, non-economic perspective. Second, it presents an examination of virtual water trade patterns in relation to the internal factors of a water-scarce country. Third, it gives the first-ever study that uses an empirical correlation between virtual water import and water scarcity to forecast likely future changes in international trade given population growth and associated water scarcity increase. Finally, for the first time, this work assesses the comparative advantage and disadvantage in a global study including all main crops and many countries whereas other comparative advantage studies are mostly limited to a few crops and a few countries.

Tunisia is used as a case study in Chapters 2 and 3, and is also one of the 42 most water-scare countries considered in Chapter 4. It is worth noting that although water scarcity is not found to be an influencing factor of Tunisia's net import of wheat in Chapter 3, Tunisia is found to follow the curve shape of the relation between the historic changes in per capita water availability and import of staple crops. This can be explained by the fact that Chapter 4 includes more crops and a longer study period. Besides, population is found to explain a significant share of net import of wheat in Chapter 3; in that sense the findings of the two chapters are consistent, because population growth is a main driver behind water scarcity and is included in Chapter 4 where water availability per country is expressed per capita.

Looking at water allocation and trade from a case study perspective was useful for a number of reasons. First, it is crucial to understand the relation between a country's agricultural policy and the impact on its water use. Most water-scarce countries, like Tunisia, still have an agricultural policy that is not adapted to its water situation, since Tunisia is still giving subsidies and other forms of financial support to farmers for growing cereals to reach self-sufficiency and reduce import. Adopting the virtual water concept in their water planning could increase the efficiency of water allocation greatly.

6.2. Limitations and future research outlook

There are a number of limitations of the current work that could be improved upon in future studies. By considering EWP and ELP as the multiplication of physical productivities and prices, we considered average productivities rather than marginal productivities. Marginal land and water productivities are expected to be lower than average land and water productivities. It would be worthwhile exploring a few of the questions posed in this thesis while adopting a marginal productivity perspective. The type of work undertaken in this thesis could further benefit from increasing the spatial resolution. Water scarcity is underestimated when studied at country level and hides the water scarcity that manifests itself in some particular places within countries (Mekonnen and Hoekstra 2016). Given the relevance of scarcity of green water (Schyns et al. 2015), we recommend future studies to further evaluate the potential effect of increasing green water scarcity, or overall green-blue water scarcity, on international food trade. Furthermore, although it has been widely acknowledged that societal changes will be the main driver of food imports in the future, climate change can worsen the situation in some countries. It is therefore interesting to study the impact of climate change together with population growth in relation to future water allocation and trade.

List of References

Alcamo, J., and Henrichs, T. (2002) Critical regions: A model-based estimation of world water resources sensitive to global changes. Aquatic Sciences, 64(4): 352-362.

Abdelkader, A., Elshorbagy, A., Tuninetti, M., Laio, F., Ridolfi, L., Fahmy, H. and Hoekstra, A.Y. (2018) National water, food, and trade modeling framework: The case of Egypt. Science of The Total Environment 639, 485-496.

Aldaya, M.M., Garrido, A., Llamas, M.R., Varela-Ortega, C., Novo, P. and Casado, R.R. (2010) Water footprint and virtual water trade in Spain. eds Garrido A & Llamas MR (CRC Press/Balkema).

Ali, M. and Byerlee, D. (2002) Productivity growth and resource degradation in Pakistan's Punjab: A decomposition analysis. Economic Development and Cultural Change 50(4), 839-863.

Allan, J.A. (1998) Virtual Water: A strategic resource global solutions to regional deficits. Ground Water 36(4), 545-546.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., W, a B. (1998) Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56. Irrig. Drain.

Alnasrawi, A. (2001) Iraq: Economic Sanctions and Consequences, 1990-2000. Third World Quarterly 22(2), 205-218.

Antonelli, M. and Sartori, M. (2015) Unfolding the potential of the virtual water concept. What is still under debate? Environmental Science and Policy 50, 240-251.

Arnell, N.W. (2004) Climate change and global water resources: SRES emissions and socio-economic scenarios. Global Environmental Change 14(1), 31-52.

Bates, B.C., Kundzewicz, Z.W., Wu, S. and Palutikof, J.P. (eds) (2008) Climate change and water. Technical Paper of the Intergovernmental Panel on Climate Change, IPCC Secretariat, Geneva.

Batjes, N.H. (2012) ISRIC-WISE derived soil properties on a 5 by 5 arc-minutes global grid (ver. 1.2). Report 2012/01, ISRIC - World Soil Information, Wageningen, the Netherlands, www.isric.org.

Bouman, B.A.M. (2007) A conceptual framework for the improvement of crop water productivity at different spatial scales. Agricultural Systems 93(1), 43-60.

Carr, M.K.V. (2013) Crop Yield Response to Water. FAO Irrigation and Drainage Paper 66. By P. Steduto, T. C. Hsiao, E. Fereres and D. Raes. Rome, Italy: Food and Agriculture Organization of the United Nations (2012), pp. 500. Experimental Agriculture 49, 311-311. http://www.fao.org/docrep/016/i2800e/i2800e00.htm.

Chahed, J., Besbes, M. and Hamdane, A. (2011) Alleviating water scarcity by optimizing "Green Virtual-Water": the case of Tunisia, In: Hoekstra, A.Y., Aldaya, M.M. and Avril, B. (eds.) Proceedings of the ESF Strategic Workshop on accounting for water scarcity and pollution in the rules of international trade, Amsterdam, 25-26 November 2010. Value of Water Research Report Series No. 54, UNESCO-IHE, Delft, the Netherlands, pp. 99-113.

Chahed, J., Hamdane, A. and Besbes, M. (2008) A comprehensive water balance of Tunisia: blue water, green water and virtual water. Water International, 33(4): 415-424.

Chapagain, A.K. and Hoekstra, A.Y. (2004) Water footprints of nations, Value of Water Research Report Series No.16, UNESCO-IHE. Delft, The Netherlands.

Chapagain, A.K. and Hoekstra, A.Y. (2008) The global component of freshwater demand and supply: an assessment of virtual water flows between nations as a result of trade in agricultural and industrial products. Water International 33(1), 19-32.

Chapagain, A.K., Hoekstra, A.Y. and Savenije, H.H.G. (2006) Water saving through international trade of agricultural products. Hydrology and Earth System Sciences 10(3), 455-468.

Chebil, A., Frija, A. and Thabet, C. (2010) Irrigation water pricing between governmental policies and farmers' perception: Implications for green-houses horticultural production in Teboulba (Tunisia). Agricultural Economics Review, 11(2): 44-54.

Chelbi, I. Kaabi, B. Béjaoui, M. Derbali, M. and Zhioua E. (2009) Spatial Correlation Between PhlebotomuspapatasiScopoli (Diptera: Psychodidae) and Incidence of Zoonotic Cutaneous Leishmaniasis in Tunisia. Journal of Medical Entomology 46(2): 400-402.

Chouchane, H., Hoekstra, A.Y., Krol, M.S. and Mekonnen, M.M. (2015) The water footprint of Tunisia from an economic perspective. Ecological Indicators 52, 311-319.

Chouchane, H., Krol, M.S. and Hoekstra, A.Y. (2018) Expected increase in staple crop imports in water-scarce countries in 2050. Water Research X 1, 100001.

Chukalla, A.D., Krol, M.S. and Hoekstra, A.Y. (2015) Green and blue water footprint reduction in irrigated agriculture: effect of irrigation techniques, irrigation strategies and mulching. Hydrology and Earth System Sciences. 19(12), 4877-4891.

Cook, S., Gichuki, F. and Turral, H. (2006) Water productivity: estimation at plot, farm and basin scale. Basin Focal Project Working Paper No. 2, GGIAR Challenge Program on Water and Food.

Davis, K.F., Chiarelli, D.D., Rulli, M.C., Chhatre, A., Richter, B., Singh, D. and DeFries, R. (2018) Alternative cereals can improve water use and nutrient supply in India. Science Advances 4(7), eaao1108.

Davis, K.F., Gephart, J.A. and Gunda, T. (2016) Sustaining food self-sufficiency of a nation: The case of Sri Lankan rice production and related water and fertilizer demands. Ambio 45(3), 302-312.

Davis, K.F., Rulli, M.C., Garrassino, F., Chiarelli, D., Seveso, A. and D'Odorico, P. (2017) Water limits to closing yield gaps. Advances in Water Resources 99, 67-75.

Davis, K.F., Rulli, M.C., Seveso, A. and D'Odorico, P. (2017a) Increased food production and reduced water use through optimized crop distribution. Nature Geoscience 10(12), 919-924.

Davis, K.F., Seveso, A., Rulli, M.C. and D'Odorico, P. (2017b) Water savings of crop redistribution in the united states. Water 9(2), 83.

Doorenbos, J. and Kassam, A.H. (1979) Yield response to water, FAO Drainage and Irrigation Paper 33, Food and Agriculture Organization, Rome, Italy.

Evans, R.G. and Sadler, E.J. (2008) Methods and technologies to improve efficiency of water use. Water Resources Research 44(7).

Fader, M., Gerten, D., Thammer, M., Heinke, J., Lotze-Campen, H., Lucht, W., Cramer, W. (2011) Internal and external green-blue agricultural water footprints of nations, and related water and land savings through trade. Hydrology and Earth System Sciences 15, 1641-1660.
Falkenmark, M. (1989) The massive water scarcity now threatening Africa: why isn't it being addressed? Ambio 18(2), 112-118.
Fan, M., Shen, J., Yuan, L., Jiang, R., Chen, X., Davies, W.J. and Zhang, F. (2012) Improving crop productivity and resource use efficiency to ensure food security and environmental quality in China. Journal of Experimental Botany 63(1), 13-24.
FAO (2003) Review of world water resources by country, Water Reports 23. Food and Agriculture Organization of the United Nations. Rome, Italy. .
FAO (2009) FAOSTAT on-line database, Food and Agriculture Organization, Rome, Italy, http://faostat.fao.org
FAO (2012) Cropping with water scarcity, FAO water report No. 38, Food and Agriculture Organization, Rome, Italy.
FAO (2015) FAOSTAT Online Database. Statistics Division, Food and Agriculture Organization of the United Nations (FAO), Rome, Italy
FAO (2016) Coping with water scarcity in agriculture a global framework for action in a changing climate. Food and Agriculture Organization of the United Nations, Rome, Italy.
FAO (2018) AQUASTAT database. Food and Agriculture Organization of the United Nations, Rome, Italy, http://www.fao.org/nr/water/aquastat/main/index.stm.
FAO, IFAD and WFP (2015) The State of Food Insecurity in the World: Meeting the 2015 international hunger targets: taking stock of uneven progress. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.
FAOSTAT (2015) Statistics Division. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.
Fracasso, A., Sartori, M., Schiavo, S. (2016) Determinants of virtual water flows in the Mediterranean. Science of The Total Environment 543, Part B, 1054-1062.
Frija, I., Frija, A., Chebil, A., Cheikh M'Hamed, H., Speelman, S., and Makhlouf, M. (2014) Marginal water productivity of irrigated durum wheat in semi-arid Tunisia, Journal of Agricultural Science, 6(10): 84-95.
Garrido, A., Llamas, M.R., Varela-Ortega, C., Novo, P., Rodríguez-Casado, R. and Aldaya, M.M. (2010) Water footprint and virtual water trade in Spain: policy implications. Springer, New York, USA.
Gerten, D., Heinke, J., Hoff, H., Biemans, H., Fader, M. and Waha, K. (2011) Global Water Availability and Requirements for Future Food Production. Journal of Hydrometeorology 12(5), 885-899.
Gilland, B. (2002) World population and food supply - Can food production keep pace with population growth in the next half-century? Food Policy 27(1), 47-63.
Gleick, P.H. (2003) Global Freshwater Resources: Soft-Path Solutions for the 21st Century. Science 302(5650), 1524-1528.
Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M. and Toulmin, C. (2010) Food security: the challenge of feeding 9 billion people. Science 327(5967), 812.

Gow, J. and Parton, K. (1995) Evolution of Kenyan agricultural policy. Development Southern Africa 12(4), 467-479.
Greenwood, D.J., Zhang, K., Hilton, H.W. and Thompson, A.J. (2010) Opportunities for improving irrigation efficiency with quantitative models, soil water sensors and wireless technology. Journal of Agricultural Science 148(1), 1-16.
Guan, D. and Hubacek, K. (2007) Assessment of regional trade and virtual water flows in China. Ecological Economics 61(1), 159-170.
Gupta, R. and Seth, A. (2007) A review of resource conserving technologies for sustainable management of the rice–wheat cropping systems of the Indo-Gangetic plains (IGP). Crop Protection 26(3), 436-447.
Han, M.Y., Chen, G.Q. and Li, Y.L. (2018) Global water transfers embodied in international trade: Tracking imbalanced and inefficient flows. Journal of Cleaner Production 184, 50-64.
Hanasaki, N., Inuzuka, T., Kanae, S. and Oki, T. (2010) An estimation of global virtual water flow and sources of water withdrawal for major crops and livestock products using a global hydrological model. Journal of Hydrology 384, 232-244.
Hanjra, M.A. and Qureshi, M.E. (2010) Global water crisis and future food security in an era of climate change. Food Policy 35(5), 365-377.
Harris, I., Jones, P.D., Osborn, T.J., Lister, D.H. (2014) Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. International Journal of Climatology 34, 623-642.
Heckscher, E.F. (1919) The effect of foreign trade on the distribution of income. Ekonomisk Tidskrift 21, 1-32.
Hoekstra, A.Y. (2003) (ed.) Virtual water trade: Proceedings of the International Expert Meeting on Virtual Water Trade, Delft, 12-13 December 2002, Value of Water Research Report Series No.12, UNESCO-IHE, Delft, the Netherlands.
Hoekstra, A.Y. (2013) The water footprint of modern consumer society, Earthscan, from Routledge, London; New York.
Hoekstra, A.Y. (2014) Sustainable, efficient, and equitable water use: the three pillars under wise freshwater allocation. Wiley Interdisciplinary Reviews: Water 1(1), 31-40.
Hoekstra, A.Y. (2017) Water footprint assessment: evolvement of a new research field. Water Resources Management 31(10), 3061-3081.
Hoekstra, A.Y. and Hung, P.Q. (2005) Globalisation of water resources: international virtual water flows in relation to crop trade. Global Environmental Change 15(1), 45-56.
Hoekstra, A.Y. and Mekonnen, M.M. (2012) The water footprint of humanity. Proceedings of the National Academy of Sciences, 109(9): 3232–3237.
Hoekstra, A.Y., Chapagain, A.K., Aldaya, M.M. and Mekonnen, M.M. (2011) The water footprint assessment manual: Setting the global standard, Earthscan, London, UK.
Hoekstra, A.Y., Hung, P.Q. (2005) Globalisation of water resources: Global virtual water flows in relation to international crop trade. Elsevier.
Hoekstra, A.Y., Mekonnen, M.M., Chapagain, A.K., Mathews, R.E. and Richter, B.D. (2012) Global monthly water scarcity: Blue water footprints versus blue water availability. PLoS ONE 7(2): e32688.

Igbadun, H.E, Mahoo, H.F, Tarimo, A.K.P.R and Salim, B.A (2006) Crop water productivity of an irrigated maize crop in Mkoji sub-catchment of the great Ruaha River Basin, Tanzania. Agricultural Water Management, 85: 141-150.

Jalava, M., Kummu, M., Porkka, M., Siebert, S. and Varis, O. (2014) Diet change—a solution to reduce water use? Environmental Research Letters 9(7), 074016.

Jones, H.G. (2004) Irrigation scheduling: advantages and pitfalls of plant-based methods. Journal of Experimental Botany 55(407), 2427-2436.

Kate, A.B., Stefan, S. and Jonathan, A.F. (2013) Improvements in crop water productivity increase water sustainability and food security—a global analysis. Environmental Research Letters 8(2), 024030.

Kijne, J.W., Barker, R. and Molden, D. (2003) Water productivity in agriculture: limits and opportunities for development, IWMI and CABI Publisher, Wallingford, UK.

Klasen, S., Meyer, K.M., Dislich, C., Euler, M., Faust, H., Gatto, M., Hettig, E., Melati, D.N., Jaya, I.N.S., Otten, F., Pérez-Cruzado, C., Steinebach, S., Tarigan, S. and Wiegand, K. (2016) Economic and ecological trade-offs of agricultural specialization at different spatial scales. Ecological Economics 122, 111-120.

Konar, M., Evans, T.P., Levy, M., Scott, C.A., Troy, T.J., Vörösmarty, C.J. and Sivapalan, M. (2016) Water resources sustainability in a globalizing world: who uses the water? Hydrological Processes 30(18), 3330-3336.

Konar, M., Hussein, Z., Hanasaki, N., Mauzerall, D.L., Rodriguez-Iturbe, I. (2013) Virtual water trade flows and savings under climate change. Hydrology and Earth System Sciences 17, 3219-3234.

Kumar, M.D. and Singh, O.P. (2005) Virtual water in global food and water policy making: is there a need for rethinking? Water Resources Management 19(6), 759-789.

Kummu, M., Guillaume, J.H.A., de Moel, H., Eisner, S., Flörke, M., Porkka, M., Siebert, S., Veldkamp, T.I.E. and Ward, P.J. (2016) The world's road to water scarcity: shortage and stress in the 20th century and pathways towards sustainability. Scientific Reports 6, 38495-38495.

Leontief, W. (1954) Domestic production and foreign trade: the American capital position re-examined. Economia Internatiozionale 7, pp. 3-32.

Marianela F, Dieter G, Michael K, Wolfgang L, Wolfgang C. (2013) Spatial decoupling of agricultural production and consumption: quantifying dependences of countries on food imports due to domestic land and water constraints. Environmental Research Letters 8: 014046.

Marill KA. (2004) Advanced Statistics: Linear Regression, Part II: Multiple Linear Regression. Academic Emergency Medicine 11: 94-102.

McLaughlin, D. and Kinzelbach, W. (2015) Food security and sustainable resource management. Water Resources Research 51(7), 4966-4985.

Mekonnen, M.M. and Hoekstra, A.Y. (2010) The green, blue and grey water footprint of crops and derived crop products, Value of Water Research Report Series No. 47, UNESCO-IHE, Delft, The Netherlands, www.waterfootprint.org/Reports/Report47-WaterFootprintCrops-Vol1.pdf.

Mekonnen, M.M. and Hoekstra, A.Y. (2011) The green, blue and grey water footprint of crops and derived crop products. Hydrology and Earth System Sciences 15(5), 1577-1600.

Mekonnen, M.M. and Hoekstra, A.Y. (2011a) National water footprint accounts: the green, blue and grey water footprint of production and consumption, Value of Water Research Report Series No. 50, UNESCO-IHE, Delft, The Netherlands, www.waterfootprint.org/Reports/Report50-NationalWaterFootprints-Vol1.pdf.

Mekonnen, M.M. and Hoekstra, A.Y. (2011b) The green, blue and grey water footprint of crops and derived crop products. Hydrology and Earth System Sciences, 15(5): 1577-1600.

Mekonnen, M.M. and Hoekstra, A.Y. (2014) Water conservation through trade: the case of Kenya. Water International 39(4), 451-468.

Mekonnen, M.M. and Hoekstra, A.Y. (2016) Four billion people facing severe water scarcity. Science Advances 2(2), e1500323.

Mekonnen, M.M., Hoekstra, A.Y. (2014) Water conservation through trade: the case of Kenya. Water Int 39, 451-468.

Mekonnen, M.M., Hoekstra, A.Y., (2011) The green, blue and grey water footprint of crops and derived crop products. Hydrology and Earth System Sciences 15, 1577-1600.

Melorose, J., Perroy, R., Careas, S. (2015) World Population Prospects: The 2015 Revision, Key Findings and Advance Tables. Working Paper No. ESA/P/WP.241, pp. 1-59.

Ministry of Agriculture (1981-2010a) Yearbooks of land use, Tunis, Tunisia (in French).

Ministry of Agriculture (1981-2010b) Yearbooks of water resources, General Directorate of Water Resources, Tunis, Tunisia (in French).

Ministry of Agriculture (2000) Dates cultivation and irrigation technics, Agency of Vulgarisation and agricultural training, Tunis, Tunisia (in French).

Ministry of Agriculture (2002) Ninth plan of development (1997-2001) (French), Tunis, Tunisia.

Ministry of Agriculture (2005a) Yearbook of surface water resources (French), General Directorate of Water Resources, Tunis, Tunisia.

Ministry of Agriculture (2005b) Yearbook of groundwater resources (French), General Directorate of Water Resources, Tunis, Tunisia.

Ministry of Agriculture (2007a) Wheat cultivation and irrigation technics, Agency of Vulgarisation and agricultural training, Tunis, Tunisia (in French).

Ministry of Agriculture (2007b) Olives cultivation and irrigation technics, Agency of Vulgarisation and Agricultural Training, Tunis, Tunisia (in French).

Ministry of Agriculture (2009) Season potatoes cultivation, Technical Center of Potatoes, Tunis, Tunisia (in French).

Ministry of Agriculture (2010a) Barley cultivation and irrigation technics, Agency of vulgarisation and agricultural training, Tunis, Tunisia (in French).

Ministry of Agriculture (2010b) Season tomatoes cultivation, Agency of vulgarisation and agricultural training, Tunis, Tunisia. (in French).

Ministry of Agriculture (2011) Yearbook of agricultural statistics, General Directorate of Agricultural Development Studies, Tunis, Tunisia (in Arabic).

Ministry of Agriculture (2013) Economic budget of the year 2013: Agriculture and fisheries (Arabic), Tunis, Tunisia.

Ministry of Environment (2009) Indicators for sustainable management of water resources (French), Tunis, Tunisia.

Molden, D. (2007) Water for food, Water for life: a comprehensive Assessment of Water Management in Agriculture, Earthscan London, UK, and IWMI, Colombo, Sri Lanka.

Molden, D., Oweis, T., Steduto, P., Bindraban, P., Hanjra, M.A. and Kijne, J. (2010) Improving agricultural water productivity: Between optimism and caution. Agricultural Water Management 97(4), 528-535.

Monfreda, C., Ramankutty, N., Foley, J.A. (2008) Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Global Biogeochemical Cycles 22.

Mukherjee, A., Kundu, M. and Sarkar, S. (2010) Role of irrigation and mulch on yield, evapotranspiration rate and water use pattern of tomato (Lycopersicon esculentum L.). Agricultural Water Management 98(1), 182-189.

Nouri, H., Stokvis, B., Galindo, A., Blatchford, M. and Hoekstra, A.Y. (2019) Water scarcity alleviation through water footprint reduction in agriculture: The effect of soil mulching and drip irrigation. Science of The Total Environment 653, 241-252.

Ohlin, B.G. (1933) Interregional and international trade, Harvard University Press, Cambridge.

Oki, T. and Kanae, S. (2006) Global Hydrological Cycles and World Water Resources. Science 313(5790), 1068.

Osama, S., Elkholy, M. and Kansoh, R.M. (2017) Optimization of the cropping pattern in Egypt. Alexandria Engineering Journal 56(4), 557-566.

Ouji, A., Rouaissi, M. and Ben Salem, M. (2010) Dual purpose barley (Hordeum vulgare L.) varietal behaviour. INRAT Annu.

Owusu-Sekyere, E., Jordaan, H. and Chouchane, H. (2017) Evaluation of water footprint and economic water productivities of dairy products of South Africa. Ecological Indicators 83(Supplement C), 32-40.

Palanisami, K ., Senthilvel, S., Ranganathan, C.R. , Ramesh, T. (2006) Water productivity at different scales under canal, tank and well irrigation systems, Centre for Agricultural and Rural Development Studies, Tamil Nadu Agricultural University, Coimbatore, India.

Parry, M.L., Rosenzweig, C., Iglesias, A., Livermore, M. and Fischer, G. (2004) Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Global Environmental Change 14(1), 53-67.

Pereira L.S., Cordery I., Iacovides I. (2009) Coping with water scarcity: Addressing the challenges, Springer, Dordrecht, the Netherlands.

Pereira, L., Cordery, I. and Iacovides, I. (2009) Coping with Water Scarcity: Addressing the Challenges, Springer, Dordrecht, 2009, p. 382.

Pereira, L.S., Cordery, I. and Iacovides, I. (2012) Improved indicators of water use performance and productivity for sustainable water conservation and saving. Agricultural Water Management 108, 39-51.

Perkins, J.H. (1993) Cuba, Mexico, and India: Technical and social changes in agriculture during political economic crisis. Agriculture and Human Values 10(3), 75-90.

Playan, E., Matoes, L. (2006) Modernization and optimization of irrigation systems to increase water productivity. Agricultural Water Management, 80: 100-116.

Portmann, F.T., Siebert, S., Döll, P. (2010) MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Global Biogeochemical Cycles 24.

Ramirez-Vallejo, J. and Rogers, P. (2004) Virtual water flows and trade liberalization. Water Science and Technology 49(7), 25-32.

Ricardo, D. (1821) On the principles of political economy, and taxation, John Murray, London, UK.

Rodrigues, G.C., Pereira, L.S. (2009) Assessing economic impacts of deficit irrigation as related to water productivity and water costs. Biosystems Engeneering, 103: 536-551.

Sadler, E.J., Evans, R.G., Stone, K.C. and Camp, C.R. (2005) Opportunities for conservation with precision irrigation. Journal of Soil and Water Conservation 60(6), 371-378.

Schewe, J., Heinke, J., Gerten, D., Haddeland, I., Arnell, N.W., Clark, D.B., Dankers, R., Eisner, S., Fekete, B.M., Colón-González, F.J., Gosling, S.N., Kim, H., Liu, X., Masaki, Y., Portmann, F.T., Satoh, Y., Stacke, T., Tang, Q., Wada, Y., Wisser, D., Albrecht, T., Frieler, K., Piontek, F., Warszawski, L. and Kabat, P. (2014) Multimodel assessment of water scarcity under climate change. Proceedings of the National Academy of Sciences 111(9), 3245-3250.

Schmidhuber, J. and Tubiello, F.N. (2007) Global food security under climate change. Proceedings of the National Academy of Sciences 104(50), 19703-19708.

Schyns, J.F. and Hoekstra, A.Y. (2014) The added value of water footprint assessment for national water policy: a case study for Morocco. PLoS One 9(6), e99705.

Schyns, J.F., Hoekstra, A.Y. and Booij, M.J. (2015) Review and classification of indicators of green water availability and scarcity. Hydrology and Earth System Sciences 19(11), 4581-4608.

Singh, R.B. (2000) Environmental consequences of agricultural development: a case study from the Green Revolution state of Haryana, India. Agriculture, Ecosystems & Environment 82(1), 97-103.

Steduto, P., Raes, D., Hsiao, T.C., Fereres, E., Heng, L.K., Howell, T.A., Evett, S.R., Rojas-Lara, B.A., Farahani, H.J., Izzi, G., Oweis, T.Y., Wani, S.P., Hoogeveen, J., Geerts, S. (2009) Concepts and Applications of AquaCrop: The FAO Crop Water Productivity Model, in: Cao, W., White, J.W., Wang, E. (Eds.), Crop Modeling and Decision Support. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 175-191.

Sun, S.K., Song, J.F., Wang, F.F., Wu, P.T. and Wang, Y.B. (2019) Evaluating the impacts of socio-economic factors on regional grain virtual water flows in China using a structural equation modeling approach. Journal of Hydrology 571, 132-141.

Tamea, S., Carr, J.A., Laio, F. and Ridolfi, L. (2014) Drivers of the virtual water trade. Water Resources Research 50(1), 17-28.

Teixeira, A.H. de C., Bastiaanssen, W.G.M., Moura, M.S.B., Soares, J.M., Ahmad, M.D. and Bos, M.G. (2008) Energy and water balance measurement for water productivity analysis in irrigated mango trees, Northeast Brazil. Agricultural and Forest Meteorology, 148: 1524-1537.

Thornton, P.K., Kristjanson, P., Förch, W., Barahona, C., Cramer, L. and Pradhan, S. (2018) Is agricultural adaptation to global change in lower-income countries on track to meet the future food production challenge? Global Environmental Change 52, 37-48.

Tilman, D., Balzer, C., Hill, J. and Befort, B.L. (2011) Global food demand and the sustainable intensification of agriculture. Proceedings of the National Academy of Sciences 108(50), 20260-20264.

United Nations (2015) World Population Prospects: The 2015 Revision. Working Paper No. ESA/P/WP.241, Department of Economic and Social Affairs, Population Division, United Nations, New York.

Van Halsema, G.E. and Vincent, L. (2012) Efficiency and productivity terms for water management: A matter of contextual relativism versus general absolutism. Agricultural Water Management 108, 9-15.

Vanham, D., Hoekstra, A.Y. and Bidoglio, G. (2013) Potential water saving through changes in European diets. Environ Int 61, 45-56.

Vanuytrecht, E., Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., Heng, L.K., Garcia Vila, M., Mejias Moreno, P., 2014. AquaCrop: FAO's crop water productivity and yield response model. Environmental Modelling & Software 62, 351-360.

Vazifedoust, M., Van Dam, J.C., Feddes, R.A. and Feizi, M. (2008) Increasing water productivity of irrigated crops under limited water supply at field scale. Agricultural Water Management, 95: 89-102.

Verma, S., Kampman, D.A., van der Zaag, P. and Hoekstra, A.Y. (2009) Going against the flow: A critical analysis of inter-state virtual water trade in the context of India's National River Linking Program. Physics and Chemistry of the Earth, Parts A/B/C 34(4–5), 261-269.

Vörösmarty, C.J., Green, P., Salisbury, J. and Lammers, R.B. (2000) Global water resources: vulnerability from climate change and population growth. Science 289(5477), 284-288.

Vörösmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S.E., Sullivan, C.A., Liermann, C.R. and Davies, P.M. (2010) Global threats to human water security and river biodiversity. Nature 467, 555.

Wada, Y., Gleeson, T. and Esnault, L. (2014) Wedge approach to water stress. Nature Geoscience 7, 615.

Wada, Y., van Beek, L.P.H., Viviroli, D., Dürr, H.H., Weingartner, R. and Bierkens, M.F.P. (2011) Global monthly water stress: 2. Water demand and severity of water stress. Water Resources Research 47(7).

WEF (2019) The Global Risks Report 2019. World Economic Forum, Geneva, Switzerland.

World Bank (2016) Data retrieved November 7, 2016, from World Development Indicators Online (WDI) database.

Yang, H. and Zehnder, A.J.B. (2002) Water scarcity and food import: a case study for southern Mediterranean countries. World Development 30(8), 1413-1430.

Yang, H., Reichert, P., Abbaspour, K.C. and Zehnder, A.J. (2003) A water resources threshold and its implications for food security. Environmental Science & Technology 37(14), 3048-3054.

Yang, H., Wang, L., Abbaspour, K.C. and Zehnder, A.J.B. (2006) Virtual water trade: an assessment of water use efficiency in the international food trade. Hydrology and Earth System Sciences 10(3), 443-454.

Yang, H., Zehnder, A. (2007) "Virtual water": An unfolding concept in integrated water resources management. Water Resources Research 43, W12301.

Ye, Q., Li, Y., Zhuo, L., Zhang, W., Xiong, W., Wang, C. and Wang, P. (2018) Optimal allocation of physical water resources integrated with virtual water trade in water scarce regions: A case study for Beijing, China. Water Res 129, 264-276.

Zhang, Y., Zhang, J., Tang, G., Chen, M. and Wang, L. (2016) Virtual water flows in the international trade of agricultural products of China. Science of The Total Environment 557-558, 1-11.

Zhao, D., Hubacek, K., Feng, K., Sun, L. and Liu, J. (2019) Explaining virtual water trade: A spatial-temporal analysis of the comparative advantage of land, labor and water in China. Water Research 153, 304-314.

Zhuo, L., Mekonnen, M.M., Hoekstra, A.Y. (2016) The effect of inter-annual variability of consumption, production, trade and climate on crop-related green and blue water footprints and inter-regional virtual water trade: A study for China (1978-2008). Water Res 94, 73-85.

Zwart, S.J., Bastiaanssen, W.G.M. (2004) Review of measured crop water productivity values for irrigated wheat, rice, cotton and maize. Agricultural Water Management, 69: 115-133.

Zwart, S.J., Bastiaanssen, W.G.M. (2007) SEBAL for detecting spatial variation of water productivity and scope for improvement in eight irrigated wheat systems. Agricultural Water Management, 89: 287-296.

Zwart, S.J., Bastiaanssen, W.G.M., de Fraiture, C., Molden, D.J. (2010) A global benchmark map of water productivity for rainfed and irrigated wheat. Agricultural Water Management 97(10): 1617-1627.

List of Publications

Peer-Reviewed Journal Articles

Chouchane, H., Hoekstra, A. Y., Krol, M. S., and Mekonnen, M. M. (2015) The water footprint of Tunisia from an economic perspective. Ecological Indicators, 52, 311-319.

Ibidhi, R., Hoekstra, A.Y., Gerbens-Leenes, P.W., and **Chouchane, H.** (2107) Water, land and carbon footprints of sheep and chicken meat produced in Tunisia under different farming systems. Ecological Indicators. 77, 304-313.

Owusu-Sekyere, E., Jordaan, H., and **Chouchane, H.** (2017) Evaluation of water footprint and economic water productivities of dairy products of South Africa. Ecological Indicators, 83, 32-40.

Chouchane, H., Krol, M. S., & Hoekstra, A. Y. (2018) Virtual water trade patterns in relation to environmental and socioeconomic factors: A case study for Tunisia. Science of The Total Environment, 613–614, 287-297.

Chouchane, H., Krol, M.S. and Hoekstra, A.Y. (2018) Expected increase in staple crop imports in water-scarce countries in 2050. Water Research X 1, 100001.

Chouchane, H., Krol, M. S., & Hoekstra, A. Y. Changing global cropping patterns to minimize blue water scarcity in the world's hotspots *(Submitted)*.

Conference Abstracts

Ibidhi, R., Hoekstra, A.Y., Gerbens-Leenes, P.W., and **Chouchane, H.** (2016) Water, land and carbon footprints of lamb and chicken meat raised in Tunisia under different farming systems: A comparative study, presented at Final EURO-AGRIWAT conference, Wageningen, the Netherlands, 7-9 March.

Chouchane, H., Krol, M. S., & Hoekstra, A. Y. (2016) Virtual Water Trade in Relation to Environmental and Socio-economic Factors: A Case Study for Tunisia, presented at EGU General Assembly 2016, Vienna, Austria, 17-22 April.

Chouchane, H., Krol, M. S., & Hoekstra, A. Y. (2017) Expected increase in staple crop imports in water-scarce countries in 2050, presented at EGU General Assembly 2017, Vienna, Austria, 24-28 April.

Other

Chouchane, H., Hoekstra, A.Y., Krol, M.S. and Mekonnen, M.M. (2013) Water footprint of Tunisia from an economic perspective, Value of Water Research Report Series No. 61, UNESCO-IHE, Delft, the Netherlands.

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Hatem Chouchane was born on 29 September 1981 in Monastir, Tunisia. He was raised in Bizerte where he received his pre-university education. After that he moved to Mahdia to obtain his BSc in Economics and Management Sciences at the University of Economics and Management Sciences of Mahdia (2005, with distinction) and then moved to Tunis to obtain his MSc degree in Econometrics and Mathematical Economics at the University of Tunis Al Manar (2009). Hatem moved to the Netherlands in 2010, first in a research stay at the University of Twente, before he started his part-time PhD effectively in 2012 at the Water Engineering and Management Department. During his PhD, Hatem has published in international peer-reviewed journals and presented his work at international conference sessions. Besides his PhD, Hatem was working as sports journalist in a part-time position.