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Modelling the optimal cropping pattern to 2030 under different climate change scenarios: A study on Egypt

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Abstract

Climate change and heat stress are expected to worsen the issue of water scarcity that is affecting the agricultural sector, among others through increased crop prices and costs, in addition to changes in yields. A crop-mix optimisation model was developed that maximises Egypt's net revenue while lightening the impacts of climatic change throughout the study period – from 2013 to 2030. The optimal cropping pattern was obtained through iteration of the model on an annual basis using the projected values of the following variables: yield, arable land, costs, prices and consumptive water use. The model is restricted by sets of constraints concerning water and land availability. These variables were projected under different climate-change scenarios using various modelling techniques. The model improves the cropping pattern in Egypt by favouring crops that achieve high profitability while using a small amount of water for irrigation and crops that have a comparative advantage in the above-mentioned variables, while decreasing all crops that are non-profitable, that use a large amount of water for irrigation, and that are heat intolerant. As a result, the total net revenue is expected to double at the end of the term. The system of models integrated in this study establishes a platform for decision makers to examine different strategies and policies.

Key words: crop-mix optimisation; climate change; climate change scenarios; Egypt; projection to 2030

1. Introduction

Crop-mix optimisation aims at establishing the best set of crops to be cultivated over a certain period, subject to specific constraints. To achieve this, models are developed that serve different objectives: the maximisation of net revenue and the minimisation of water use, among others. The agricultural sector is the centre of this study, as it represented 11.2% of Egypt's gross domestic product (GDP) and covered 26% of its employment in 2015 (World Bank 2017). It is the sector that is affected the most by climate change (CC), and faces major challenges like water scarcity, heat waves and temperature alterations.

To lessen the negative consequences of climate change, several adaptation practices have to be considered, such as a shift to more salinity- and heat-tolerant crops, the reduction of crops that require more water, and a focus on high-value crops. Crop-mix optimisation provides an efficient tool to examine such practices. The optimisation model developed for this purpose aims at improving cropping patterns in Egypt by favouring all crops that achieve high profitability while using a smaller amount of water. Using a mathematical model that takes crop yields, areas, costs, prices and consumptive water use into consideration, the optimal crop mix for Egypt is projected to 2030 under different climate change scenarios. One of the main contributions of this work is that it offers a platform for policy makers who can assess potential policies and study their current and future impacts on different regions by providing the model with various inputs corresponding to different policies. The interlinked system of models presented in this study aims at enabling and facilitating evidence-based and quantitatively emphasised decision-making.

The paper is structured as follows. It starts by presenting the relevant literature, followed by details of the methodology employed. Subsequently, the results are discussed, before highlighting the main findings and possibilities for future work.

2. Background

The primary objective in crop-mix problems is to generate an optimal combination of crops amongst those considered, such that it maximises the total profitability while satisfying a system of constraints. Various research papers deal with crop-mix optimisation as an adaptation strategy in relation to several problems. El-Gafy (2013) utilised a mathematical model to optimise the cropping pattern in Egypt for the current year, with no consideration of future projections, by satisfying three goals: minimising water use, minimising fertiliser use, and maximising net revenue. Abdou (2003) worked on the seasonal level, trying to achieve two goals: maximising the net revenue per unit of land and maximising the net revenue per unit of water.

Similar efforts were conducted in different countries. Sarker *et al.* (1997) established a model for land allocation among competing crops in Bangladesh that maximises the contribution from agricultural activities. Furthermore, Mainuddin *et al.* (1997) employed an optimisation model to assess the quantity of water that should be allocated to the different cropping areas in Thailand. In addition, Sarker and Quaddus (2002) considered a nation-wide crop-planning problem employing a multi-objective optimisation model that satisfies different goals. A similar model was developed by Sarker and Ray (2009) to maximise gross income and minimise the required working capital. The model was constrained by demand, land, capital, area and import constraints. The above-mentioned researchers did not assess the optimal cropping pattern in the future where the impacts of climate change can be taken into consideration.

The following studies deal with the effects of climate change on the agricultural sector. A static partial equilibrium model, called the Agricultural Sector Model of Egypt (ASME), was employed with the aim to maximise consumer and producer surplus from agricultural production and water resources, although it does not examine the impacts of climate change on specific crops (McCarl *et al*. 2015). As it is a static model, it looks at the implications of climate change in the years 2030 and 2060. It was concluded that climate would affect the country's agriculture especially after 2030. The study proposed some adaptation measures; however, it did not examine them quantitatively. Eid *et al.* (2007) assessed the impacts of climate change on farm net revenue in Egypt using an economic Ricardian model. Their study revealed that high temperatures would harm Egypt's agricultural production and water resources. According to El-Ramady *et al*. (2013), Egypt is vulnerable to the impacts of climate change, including rising sea levels, and effects on water resources and socio-economic conditions. These studies, however, follow different objectives from this work. They do not project the effects of climate change on crops in Egypt, as well as on their allocation.

Several tools have been developed worldwide to project the impacts of climate change on a country's agricultural sector, among which are the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) (Rosegrant *et al*. 2012). This multimarket system of linked models simulates trade, demand, prices, yields and the global production of agricultural commodities and activities under different climate change scenarios. Ye *et al*. (2013) assessed the consequences of climate change on the yields of major crops in China using IMPACT. Several modelling techniques have been utilised by Rosegrant *et al*. (2012) to assess the consequences of different agricultural policies and technologies under a range of climate and socio-economic futures in the Philippines, such as the biophysical Decision Support System for Agro-technology Transfer (DSSAT), the Dynamic Research Evaluation for Management (DREAM) and IMPACT (Rosegrant *et al*. 2016). Xie *et al*. (2014) implemented a regional-scale assessment covering 42 sub-Saharan African countries. Their study analyses the application potential of motor pumps while considering the impacts of climate change on water resources and agricultural productivity using a crop-mix optimisation model that maximises the net revenue. This work served as an inspiration for the crop-mix model and the methodology used in this study.

Only very few studies dealt with the impacts of climate change on a country's crop mix and aim to optimise the country's cropping pattern. Even though some studies are concerned with the optimal crop-mix optimisation, its correlation with climate change and the possible future scenarios is not examined. On the other hand, several works focus on the impacts of climate change on the agriculture sector as a whole, yet in this case the issue of the optimal cropping pattern is not incorporated.

3. Methodology

To project the optimal crop mix for Egypt under climate change scenarios, we developed a crop-optimisation model to maximise the country's net revenue while being restricted by a number of constraints. To do so, the model favours those crops that achieve the highest yield and prices, while using minimal irrigation water and providing high profitability. These crops are thus assigned more cropping area than the ones that fail to meet these requirements.

The model that was developed is depicted in the equation and constraints below. A total of 26 crops are addressed in this paper, namely barley, cabbage, chickpeas, cotton, eggplant, faba beans, garlic, green peas, lentils, linen, maize, multi-cut clover, one-cut clover, onions, peanuts, pepper, potatoes, rice, sesame, soybeans, squash, sugar beet, sugarcane, tomatoes, watermelon and wheat. These crops were chosen because they represent some of the most economically crucial crops in Egypt. In addition, they represent almost 73% of the country's cropping area (Economic Affairs Sector 2013). Fruit and palm dates are not included in this study, as their planting and harvesting pattern are unique and have to be examined independently.

The crop-mix optimisation model can be described according to the equation given below.

$$\underset{A_{rct}}{\text{Maximise net revenue}} \text{ (\$/yr)} = \sum_r \sum_c [A_{rct}.(Y_{rct}.P_{rct} - TC_{rct})] \quad (1)$$

Subject to:

$\sum_c A_{rct} \leq A_{rt,max}$ (i)
$\sum_c w_{rct}.A_{rct} \leq Q_{rt}$ (ii)

$A_{rct,min} \leq A_{rct} \leq A_{rct,max} \quad \forall c$ (iii)

$A_{rct} \geq A_{rct,ss}$ for c = wheat (iv)

where:
A_{rct}: Cropping area in region *r* for crop *c* at time t (hectare)
Y_{rct}: Yield in region r for crop *c* at time *t* (ton/hectare)
P_{rct}: Price at region r for crop *c* at time *t* ($/ton)
TC_{rct}: Total of irrigation and production costs in region r for crop *c* at time *t* ($/hectare)
$A_{rt,max}$: Maximum area with irrigation potential in region *r* and time *t* (hectare)
w_{rct}: Water consumptive use in region *r* for crop *c* at time *t* (m^3/hectare-year)
Q_{rt}: Total available water for irrigation in region *r* at time *t* (m^3/year)
$A_{rct,min} = (1 - \delta_A).A_{rct,avg}$
$A_{rct,max} = (1 + \delta_A).A_{rct,avg}$
$A_{rct,avg}$: Mean cropped areas in region *r* for crop *c* for 4 years preceding $t = \frac{1}{4}\sum_{n=1}^{4} A_{rc(t-n)}$
δ_A : % of change in cropped areas through time *t* with accordance to socioeconomic needs (in this study, δ_A was chosen to be 25%)
$A_{rct,ss}$: Cropped area in region *r* for crop *c* at time *t* that achieves self-sufficiency $= \frac{Prod_{rct,ss}}{Y_{rct}}$
$Prod_{rct,ss}$: Self-sufficiency production of wheat defined as 50% of crop consumption

The model iterates on a yearly basis up until the year 2030. R software was employed to solve the model. To reflect the cropping pattern in Egypt, as well as the three agricultural seasons, the cropping area was utilised instead of employing the cultivated area.

3.1 Constraints

To reflect the abovementioned goals and create a balance between the minimisation of water use and the maximisation of profitability, the model is restricted by certain constraints, as illustrated in the equations above. Constraint (i) states that the sum of areas allocated to the different crops should be less than or equal to the overall arable area that is available at present. The total arable land available to plant the 26 chosen crops in 2013, $A_{rt,max}$, was 4 787 468 hectares (CAPMAS Yearbook 2013). The water-use constraint, constraint (ii), indicates that the sum of water resources consumed by the crops should not exceed or be equal to the total available water for irrigation, Q_{rt}. In constraint (iii), we assume that the cropping area of each crop can only change by a certain percentage over time, as it is not possible to alter the cropping pattern completely in an instant. Hence, it is necessary to bring the cropped areas under minimum and maximum bounds of cultivation (El-Gafy *et al.* 2013). In this study, we used δ_A as the maximum attainable change per year. Hence, this δ_A will hypothetically be under the control of the decision maker. Constraint (iv) deals with a special treatment of wheat. The Egyptian government wants to raise wheat self-sufficiency rates to 80% through an increase in wheat cropped area, to reach 4.2 million hectares by 2030. A different perspective argues that Egypt should focus on producing high-value crops and rather continue importing wheat and other food security crops. In this study, both alternatives are considered by establishing two different paths, one in which the model is bound by a wheat self-sufficiency constraint and the other in which wheat is treated the same way as the rest of the crops. However, in this work, wheat self-sufficiency would reach 50% upon addition of the constraint.

This percentage (50%) is held constant throughout the study period, and the cropping area satisfying this constraint changes over the course of time.

3.2 Scenarios examined

Socio-economic and emission scenarios provide a plausible description of how the future might develop with regard to various changes: socio-economic, technological, energy and land-use, and in emissions of greenhouse gases (Van Vuuren *et al*. 2011).

Climate projections are obtained following the Fifth Assessment report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), which is based on the fifth phase of the Coupled Model Inter-comparison Project, CMIP5 (IPCC 2015). Following the scenario selection methodology of IMPACT in this study, a climatic scenario incorporating representative concentration pathways (RCPs), shared socio-economic pathways (SSPs) as well as general circulation models (GCMs) is applied.

Two GCMs were chosen: the IPSL-CM4 (Institute Pierre Simon Laplace) climate model and the UKMO-HadGEM1, the global environmental model of the UK Hadley Centre for Climate Prediction and Research (Madec *et al*. 1997), as they show high accuracy concerning temperature projection, a parameter that highly affects the scope of the study (Fischer *et al*. 2005). The model runs to generate values up until 2030 under optimistic, moderate and pessimistic climate change scenarios.

Regarding the optimistic scenario, SSP1 is adopted where resource use and fossil fuel intensity will decrease (O'Neill *et al*. 2014), with RCP 2.6. For the moderate scenario, in terms of which the current trends would continue, the middle of the road (SSP2) is selected, with the same RCP 2.6. The highest emission scenario, namely RCP 8.5, symbolises the pessimistic scenario and is characterised by increasing greenhouse gas emissions over time.

3.3 Projection of variables to 2030 and their results

Different modelling techniques were deployed to project the different variables of the model under different climate change scenarios. The first step to project the different variables to 2030 is to generate the temperature projections of four scenarios for the 12 months of the year throughout the study period. Concerning the weather projections, values from the dynamic downscaling model, MarkSim (CGIAR, CCAFS, ILRI, CIAT, 2017), were employed. Figure **1** demonstrates the annual mean temperature from 2010 up until 2030 for the four examined scenarios. It can be seen that, although average temperatures are increasing at a constant rate, their percentage increase lies between 2% (IPSL RCP 2.6) and 4% (HGEM RCP 2.6; RCP 8.5).

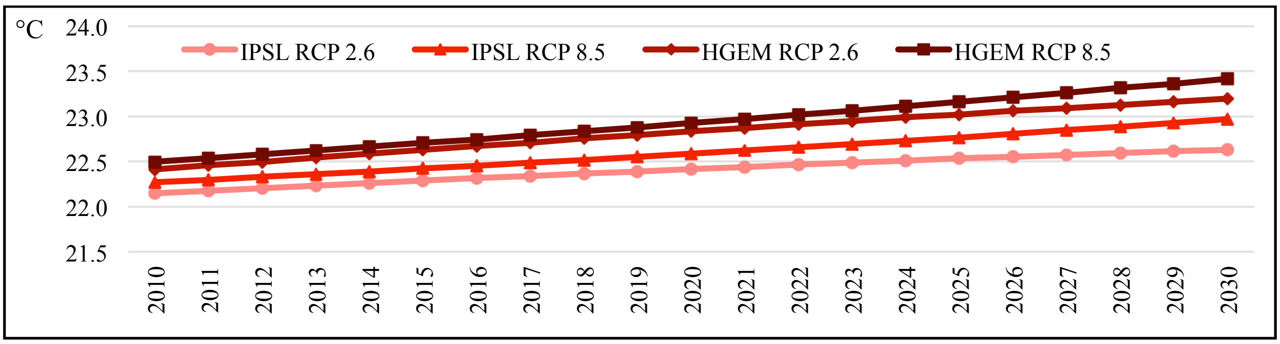

Figure 1: Temperature differences between scenarios
Source: Authors' calculations from MarkSim weather file generator

In the following sections, the projection of the variables of the model are examined in depth, namely the description and illustration of the different parameter projections are presented.

3.3.1 Cropping area, $A_{rt,max}$

The total cropping area, $A_{rt,max}$, was projected using the exponential time-series regression technique, with historical time-series data for the total cropping area from 1968 to 2013 gathered from the yearbooks of the Central Agency for Public Mobilization and Statistics (CAPMAS Yearbook 2013). Almost 73% of this projected total cropping area was used as the value of the $A_{rt,max}$ constraint.

shows that the cropping area increases throughout the projected period, reaching 7.7 million hectares in 2030.

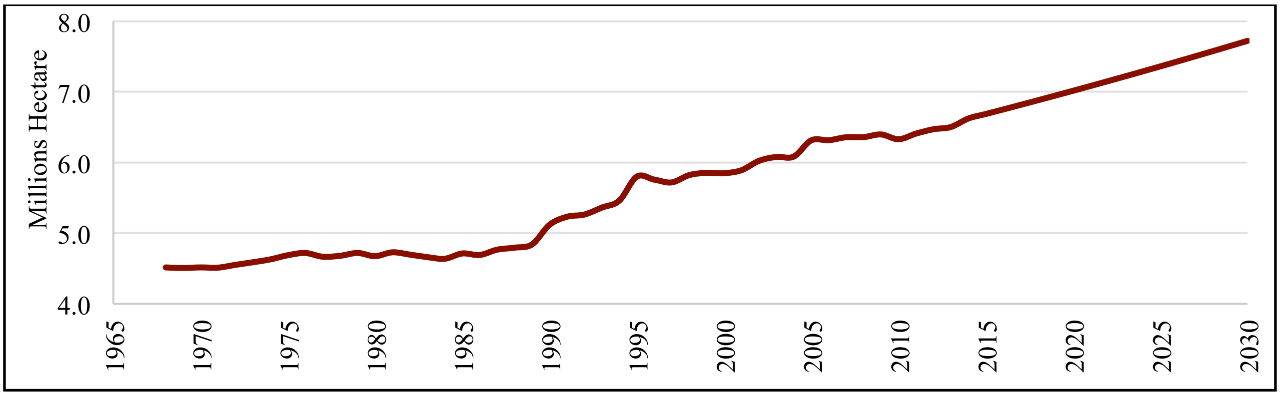

Figure 2: Actual and projected cropping area
Source: Authors' calculations based on data from CAPMAS

3.3.2 Water available for irrigation, Q_{rt}

In this study, water resources were calculated at the level of the field. Under all climate change scenarios, where no policy measures are implemented in the Nile Basin, the water available for irrigation will not be changed. Previous studies conducted in the Nile Basin demonstrate that its water resources will not be reduced before the middle of the century. Beynene *et al.* (2010) deduced that, in their study period from 2010 to 2039, an increase in the streamflow of the Nile will occur, resulting from a general increase in precipitation. Therefore, for the purpose of this research, water available for irrigation is assumed to be constant throughout the entire study period.

To calculate Egypt's Q_{rt} in 2013, the water consumptive use of each crop was multiplied by its cropped area in 2013, and these values are then summed for the 26 crops to generate the water available for irrigation, which reaches a value of 37.5 billion m^3 in this study.

3.3.3 Crop water consumptive use, W_{rct}

Crop water consumptive use, W_{rct}, is the amount of water needed by a crop to live and grow, from the date of planting until the date of harvesting and including transpiration and evaporation (Brower & Heibloem 1986). For this paper, water consumptive-use projections were generated using the CropWat 8.0 software developed by the Land and Water Management Division of the Food and Agriculture Organization (FAO) (Allen *et al*. 1998; FAO 2006). Water requirements per crop were projected under four scenarios (IPSL RCP 2.6, IPSL RCP 8.5, HGEM RCP 2.6 and HGEM RCP 8.5). The projected water consumptive use of different crops exhibit similarity in terms of high water consumption under the two pessimistic scenarios. As shown in

, maize is one of the crops that consume more water to grow under the pessimistic HGEM scenario.

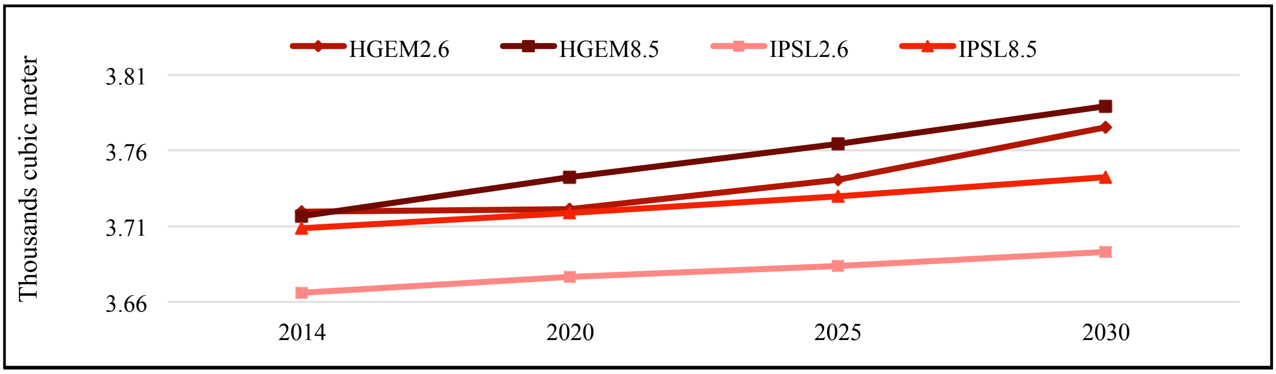

Figure 3: Water consumptive use of maize in the different scenarios
Source: Authors' calculations from CropWat 8.0 software.

Other crops, such as wheat, follow different patterns, as shown in Figure 1, in terms of which they have a greater water consumptive use under IPSL RCP 8.5 than what is needed under HGEM RCP 8.5. Both patterns are justifiable, since these are the two most pessimistic scenarios in terms of temperature, and thus the crops under these scenarios require more irrigation water.

It can be seen that water requirements per crop tend to increase for all crops under the different scenarios, mainly due to the temperature increase over the years and keeping other factors at 2013 levels. Moreover, improvements in technology, such as improved varieties and better irrigation techniques among others, would change the results of the projection should they occur. The increase in crop water consumptive use is not substantial, mainly due to the length of the study period and the resulting increase in the projected temperatures.

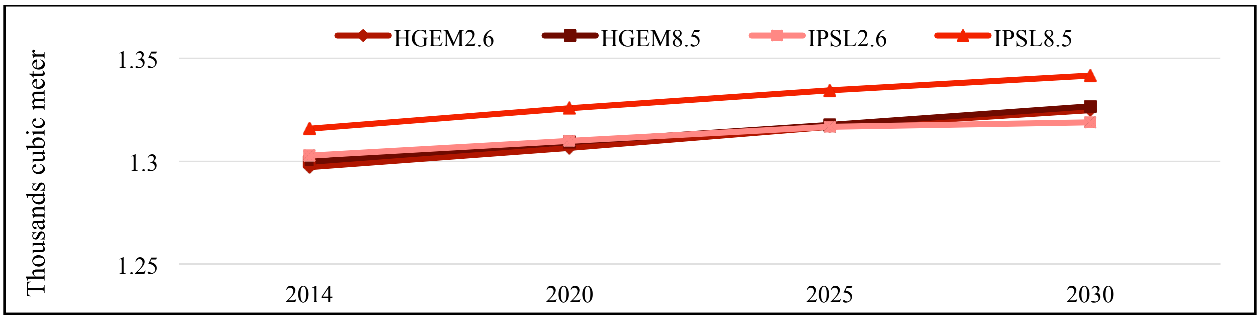

Figure 1: Water consumptive use of wheat in the different scenarios
Source: Authors' calculations from CropWat 8.0 software

3.3.4 Prices, P_{rct}

As a first step, historical time-series data of the prices of 26 crops in Egypt over the period from 1965 to 2013 was gathered from the FAO (2017) to predict the future prices of these crops to 2030 using exponential and linear time-series regression. The IMPACT multimarket model takes into consideration the effect of climate change on all the variables simultaneously and predicts the effects of climate change on the world prices of crops using different climate change scenarios. The second step was to build an econometric relationship between the world price of each crop predicted by IMPACT, and the price of that crop in Egypt, which was predicted in the first step. As a final step, the estimated relationship is utilised to project prices of crops in Egypt under six different climate change scenarios. However, we assume for simplicity that production volumes will have no impact on prices. This assumption is examined by estimating the price transmission elasticities of crops in Egypt. Unit root tests for all the variables, using the augmented Dicky Fuller test (ADF), suggest that most of the variables are nonstationary in levels, but stationary in first difference, $I(1)$, variables. In addition, Engle-Granger co-integration tests suggest that prices in Egypt and world prices of all crops are co-integrated. Therefore, co-integration regression using fully modified least squares (FMOLS) was performed to estimate the price transmission elasticities.[1]

Figure 5 and 6 illustrate the projected prices under the IPSL optimistic scenarios. Sugar beet experiences a high escalation, as it grows at a percentage of roughly 4.7% on an average annual basis. Following this are watermelon, of which the price rises by an average of 2% annually, after which are pepper and maize, of which the prices grow by 1.9% each per annum. On the other hand, barley and lentils experience an average annual decrease of 0.5% and 0.3% respectively.

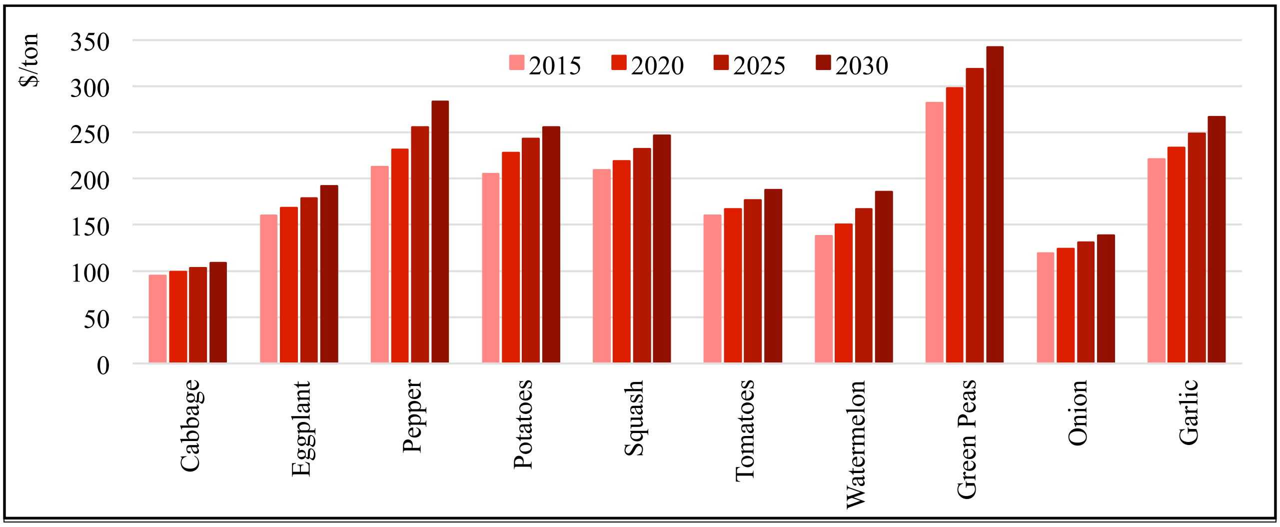

Figure 5: Nominal prices of vegetables: IPSL optimistic scenario
Source: Authors' calculations for data obtained from the FAO

According to all climate change scenarios, the prices of most crops will grow by 2030 for several reasons. Firstly, population increase will increase the demand for food, while at the same time the negative impacts of climate change on the production of crops will increase their costs and hence also their prices.

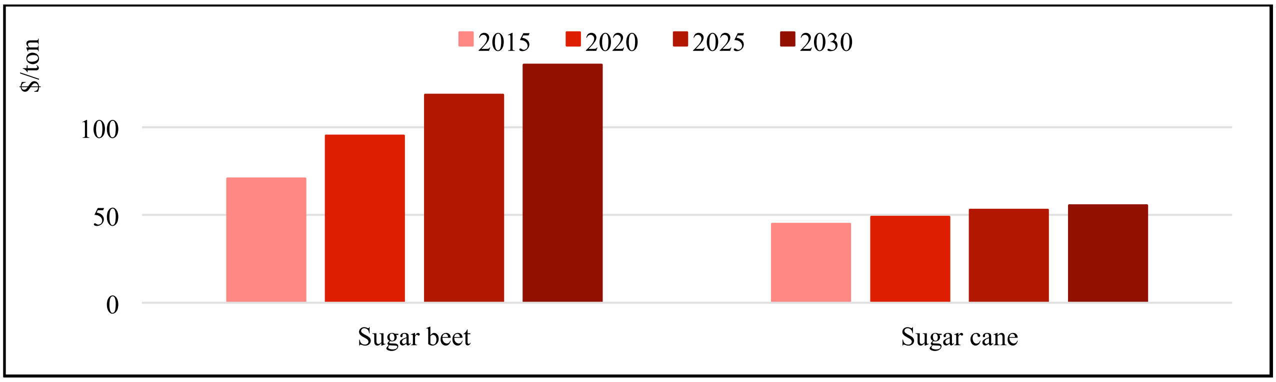

Figure 6: Nominal prices of sugar crops: IPSL optimistic scenario
Source: Authors' calculations for data obtained from the FAO

3.3.5 Total costs, TC_{rct}

[1] The results of the mentioned tests are available upon request.

It was assumed that the effects of climate change on the costs of different crops will be the same as their effect on prices. Therefore, cost projection was undertaken in two steps. The first operated under a hypothetical no climate change scenario, for which it was assumed that the historical time-series cost trend would continue without any shocks. To implement this step, CAPMAS data from 1995 to 2013 was used for the 26 crops to conduct a time-series regression to estimate each crop's costs until the year 2030. This was done with the econometric relationship between the world prices of each crop, which are predicted by the IMPACT model, and the prices of that crop in Egypt, which are predicted in the first step of the price projection. The second step is based on the assumption that the effects of climate change on costs is equal to its effects on prices. Hence, the abovementioned crop-specific growth rates were applied to the estimated costs that were derived from the first step to reflect the possible effect of climate change on crop costs.

Figure 7 illustrates the trends of six crops – three crops of which the growth rates are highest, as well as those of which the growth rates are lowest in comparison to the rest of the crops, starting from 2014 up to 2030 under the IPSL optimistic scenario.

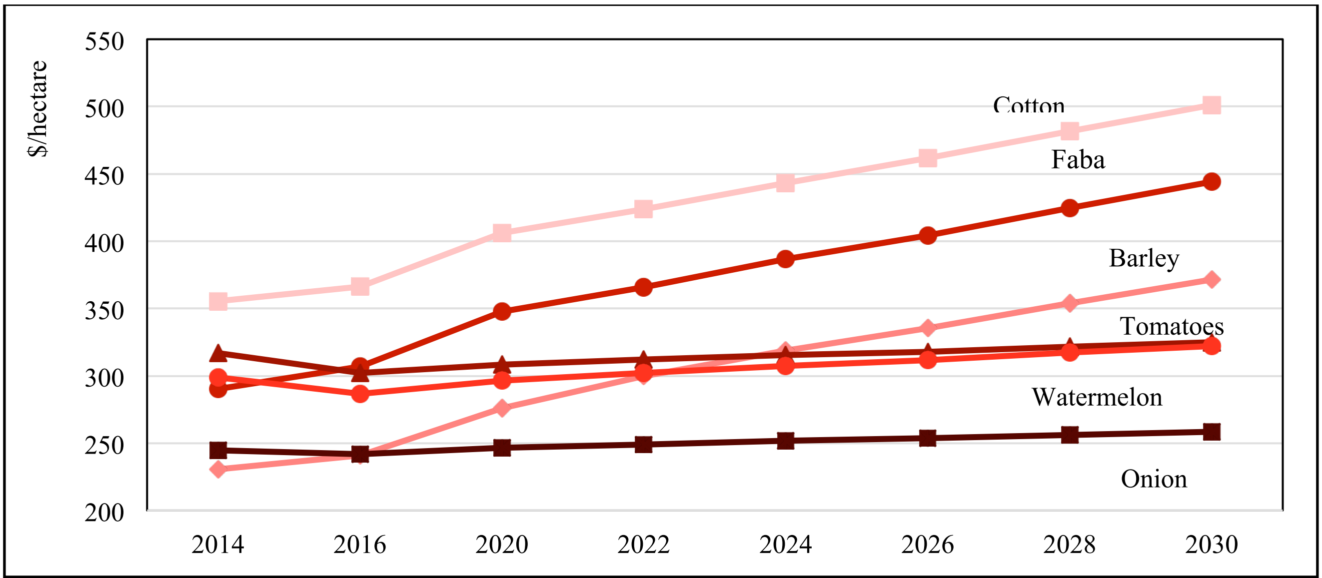

Figure 7: Costs of main crops: IPSL optimistic scenario
Source: Authors' calculations from CAPMAS data

3.3.6 Yield, Y_{rct}

Historical yield regression was employed (Thomas 2015) in the study to project the yields of 26 crops up to 2030. It follows a statistical approach to historical data. The dependent variable is the yield and the explanatory variable is a non-parametric version of the weather, time trend and prices. This method is tied directly to real data and assumes a constant relationship between yields, prices and temperatures. To generate yield projections for the different climatic and socio-economic scenarios, historical time-series yield and temperature values were obtained from the FAOSTAT database (FAO 2017) and the World Bank CC knowledge portal (World Bank, 2013). This time-series historical yield regression projects yield values under three climate change scenarios, accompanied by three socio-economic pathways from 2014 to 2030.

Projected yield values in all scenarios either increase or decrease slightly, or they remain stable. As there are no enormous temperature variations between the different scenarios, yield differences between the scenarios are not very significant.

and 9 depict the yield projections of the different crops throughout different intervals of the study period under the IPSL optimistic scenario.

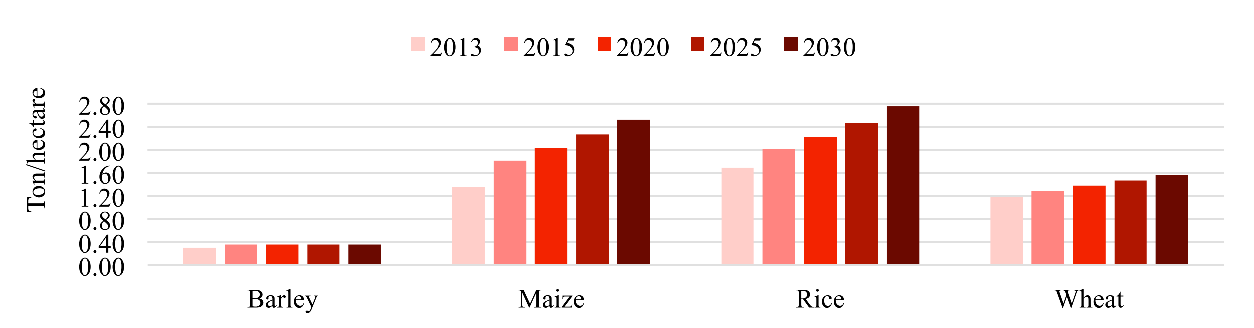

Figure 2: Yield of cereals: IPSL optimistic scenario

Source: Authors' calculations from data from the Egyptian Ministry of Agriculture

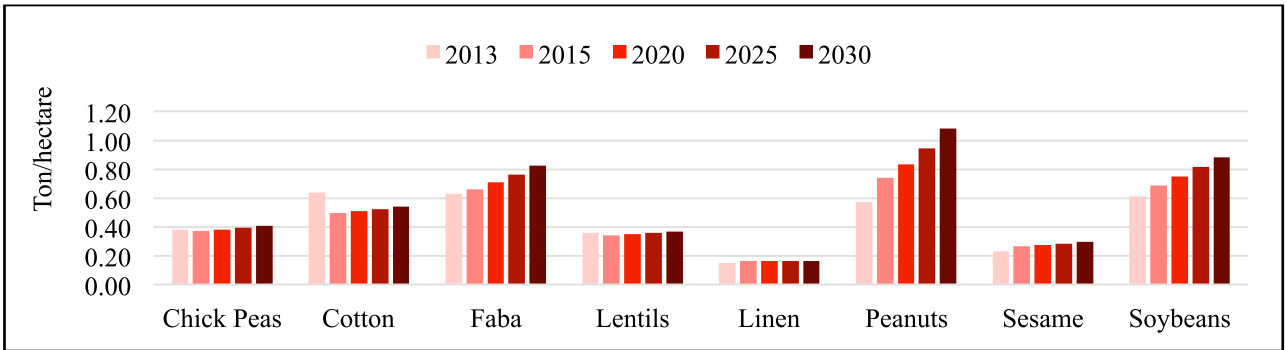

Figure 9: Yield of legumes and fibres: IPSL optimistic scenario

Source: Authors' calculations from data from the Egyptian Ministry of Agriculture

It was anticipated that, if the projected temperature of summer crops falls within the crops' temperature tolerance level, then crop yields would increase. For instance, maize, peanuts, rice, sesame and soybeans are summer crops, the yield values of which increase throughout the study period. In this case, the most pessimistic scenarios produce the highest yield results. Similarly, the yields of winter crops would decrease the higher the temperature gets. Hence, the most optimistic scenarios produce the highest yield values. Barley and lentil yields stay stable the higher temperatures rise. The garlic yield decreases as the higher temperatures increase. Yet there are anomalies arising from these assumptions, because not only temperature plays a role in yield projection.

4. Results of crop pattern optimisation

In the following section, the results of the crop optimisation model are presented and analysed.

4.1 Overall results for optimal crop mix

One of the main goals of the model is to favour high-value crops. The output of the optimisation model for the IPSL optimistic scenario for all crops is shown in Figure 3. The figure shows an increase in the cropping areas assigned to six crops over the years. The model has promoted some crops over others due to general trends and clusters. The six prioritised crops experience an annual increase in their optimal areas of 9% to 10%, yet they stay more or less stable at the end of the study period. Moreover, the cropped areas of 14 of the crops decrease throughout the period of the study. Finally, land allocation changes enforced by the model resulted in more than a doubling of net revenue, from around $10.59 billion in 2013 to roughly $24.14 billion in 2030.

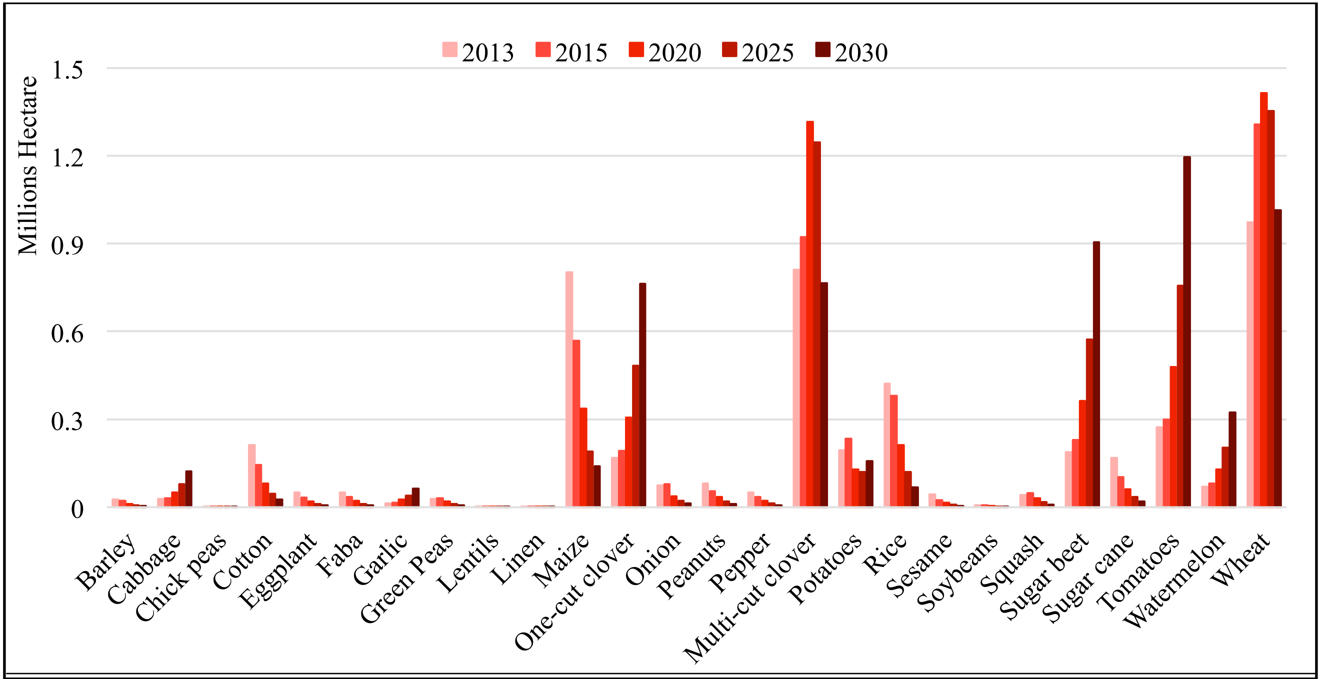

Figure 3: Optimal crop mix under IPSL optimistic scenario
Source: Authors' results

The crops generating the highest net revenue whilst consuming the least amount of water form the most beneficial group, and these include crops such as watermelon and garlic, with each generating over 6% of the average total net revenue and consume a small amount of water.

Another advantageous cluster is the group of crops using a very small amount of W_{rc} and achieving average profitability. One-cut clover, for example, produces around 4% of the total net revenue, yet is promoted by the model as it consumes the least amount of water. Among this group are also cabbage and sugar beet, which seem to have a comparable advantage due to their low water use. Although the water used by sugar beet is relatively average, it has been favoured because it is a heat-tolerant crop generating a higher net revenue than most of the crops in this group, namely 7.4% of the average net revenue. On the other hand, wheat achieves around 1% of the total net revenue but, due to the fact that its W_{rc} is notably low, it is promoted by the model.

Tomatoes produce the highest net revenue in all scenarios, reaching around 12% of the total net revenue. Even though their W_{rc} is relatively high, their cropping area increases. It can be seen that the crops chosen by the model are those with a noticeable comparative advantage in at least one of the essential parameters.

On the other hand, there are crops that decrease or stay stable throughout the study period. Three clusters can be differentiated in this regard. Despite the fact that multi-cut clover, squash, onion, rice, eggplant and sugarcane are among the most profitable crops, they are not prioritised because they consume the highest W_{rc}. As a result, the model decreases the cropping areas of these crops by an annual average of 1%, 8%, 10%, 10%, 11% and 12% respectively. Barley, chickpeas, soybeans, faba beans and lentils are among the crops using the least amount of water. However, their net revenue fall in the lowest portion, generating roughly 1% of the total gains. Hence, the model decreases their cropping areas. Crops that are not promoted are those that do not have a comparative advantage. Maize and peanuts fluctuate around the mean of both parameters and thus do not give the model a reason to favour them.

4.2 Results under different scenarios

A comparison of the scenarios considered in this study demonstrates slight differences between the different GCMs due to the length of the period examined – ending in 2030, which do not reflect a significant increase in temperature. However, variations are observed between the optimistic and pessimistic scenarios. Figure 4 plots a comparison of the net revenues of the IPSL optimistic and pessimistic scenarios.

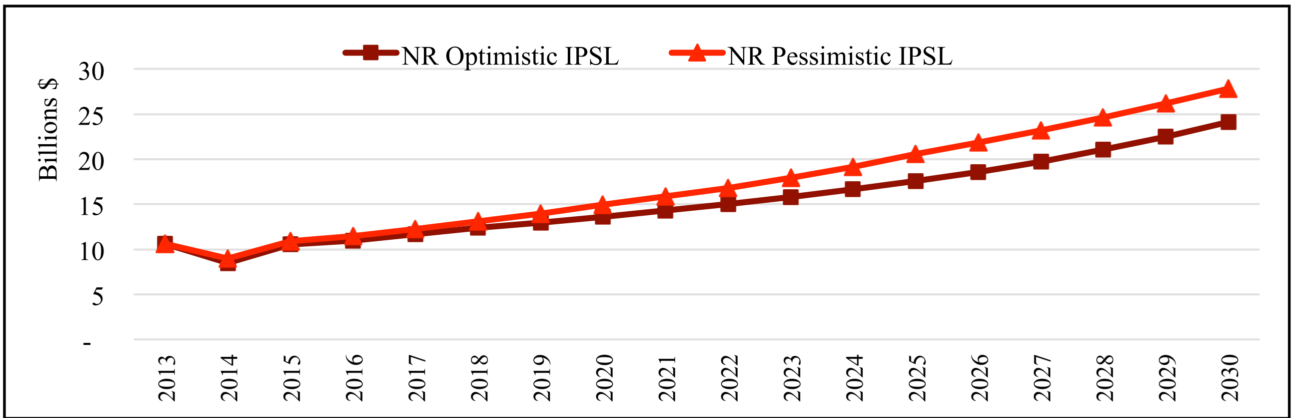

Figure 4: Net revenue of IPSL optimistic and pessimistic scenarios
Source: Authors' results

It is noted that the pessimistic scenario generates higher net revenues. This is because, in a pessimistic scenario, prices would increase more than in an optimistic one. Table 1 presents the differences between the optimal areas allocated to selected crops under the IPSL optimistic and pessimistic scenarios. Because the outcome of this GCM is similar to that of the HGEM GCM, the findings are mostly generalisable.

Table 1: Optimal areas: IPSL optimistic and pessimistic scenarios

Crops	Cropped area 2013 (hectare)	Optimistic			Pessimistic		
		Cropped area 2030 (hectare)	Annual growth rate (%)	Rate of change (%)	Cropped area 2030 (hectare)	Annual growth rate (%)	Rate of change (%)
Cabbage	27 585	123 401	9.21	347	35 760	1.54	30
Chick peas	2 091	301	-10.77	-86	1 048	-3.98	-50
Maize	80 .423	140 255	-9.75	-83	112 517	-10.91	-86
Onion	74 606	12 785	-9.86	-83	11 000	-10.65	-85
Peanuts	80 644	11 642	-10.76	-86	74 635	-0.45	-7
Multi-cut clover	810 399	765 370	-0.34	-6	409 490	-3.94	-49
Potatoes	193 955	157 068	-1.23	-19	483 343	5.52	149
Squash	42 504	9 458	-8.46	-78	5 .112	1.54	30

Source: Authors' results

It can be seen that the pessimistic scenario allocates less land to multi-cut clover and cabbage. The decrease in the cropped area of multi-cut clover is larger than that of the optimistic scenario, reaching almost half by 2030 under the pessimistic scenario, reflecting that it is not able to cope with high temperatures because it is a winter crop. Cabbage was shown not to tolerate high temperature; thus, its cropped area increases by only 1.54% annually under the pessimistic scenario versus 9% annually under the optimistic one.

On the other hand, potatoes, squash, chickpeas and peanuts have been shown to be more beneficial under the pessimistic scenario. Potatoes and squash decreased under the optimistic scenario, while they exhibited a steady increase under the pessimistic one, reaching an increase of 150% and 30%

of their allocated areas in 2013 respectively. Chickpeas and peanuts feature a decreasing trend under both scenarios; however, their rate of decline under the pessimistic scenario is much lower. The rest of the crops do not exhibit significant differences between the scenarios.

4.3 Wheat self-sufficiency constraint

Table 2 shows the cropping areas as well as the annual growth rates (2013 to 2030) of some crops that show significant differences between the presented wheat self-sufficiency constraints. Under the constraint, wheat increases from 1.4 million hectares in 2013 to 1.7 million hectares in 2022, and maintains this level until the year 2027, after which it decreases to end at 1.6 million hectares in 2030. The cropping area provided to wheat experiences an average annual growth rate of 1%, in comparison to roughly 0.2% in the case where the self-sufficiency constraint is relaxed.

Potatoes, green peas and squash benefit from the wheat self-sufficiency constraint, while the wheat self-sufficiency constraint has negative impacts on the area allocated to cabbage, one-cut clover, multi-cut clover and sugar beet. The remaining crops have not experienced major changes under the constraint. Overall, a comparison of the total profitability indicates that the addition of the wheat self-sufficiency constraint decreases the net revenue by 13.3%.

Table 2: Comparison between the wheat constraint sets: IPSL optimistic scenario

Crop	Without wheat SS constraint*			With wheat SS constraint		
	Cropped area 2013 (hectare)	Cropped area 2030 (hectare)	Annual growth rate (%)	Cropped area 2013 (hectare)	Cropped area 2030 (hectare)	Annual growth rate (%)
Cabbage	27 585	123 401	9.20	16 551	56 514	7.50
Green peas	28 448	5 955	-8.80	28 448	13 617	-4.20
Multi-cut clover	810 399	765 370	-0.30	810 399	721 699	-0.70
One-cut clover	168 930	763 085	9.30	101 358	430 143	8.90
Potatoes	193 955	157 068	-1.20	140 231	194 282	1.90
Squash	42 504	9 458	-8.50	42 504	26 998	-2.60
Sugar beet	188 462	904 819	9.70	113 077	647 946	10.80
Wheat	973 166	1 014 216	0.20	1 387 500	1 640 741	1.00

* SS constraint = self-sufficiency constraint
Source: Authors' results

5. Discussion

One of the main goals of the crop optimisation model is to lessen the impacts of climate change by increasing the cropped area of crops that are heat tolerant, thus generating high profitability while consuming a small amount of water. By increasing such high-value crops, Egypt would be able to mitigate several climate-induced losses.

Furthermore, one of the main achievements of the model is the substitution of sugarcane with sugar beet to produce raw sugar. It is well known that sugarcane consumes the highest amount of irrigation water, while sugar beet is a heat-tolerant and profitable crop that needs less watering. Although sugar is still derived primarily from sugarcane, sugar beet makes a feasible alternative.

Another important and plausible result of the model is the reduction in the cropped area of rice. This is mainly because it is a high water-consumptive crop that is still planted extensively in Egypt. It is often believed that rice is one of the most crucial crops for Egyptian farmers. Hence, the Egyptian government will need to offer alternative rice varieties that consume less irrigation water.

The addition of the wheat self-sufficiency constraint demonstrates that the proposed crop optimisation model is flexible, can incorporate government interventions and suggested policies, and can examine their impacts. To illustrate, faba beans are a nationally crucial foodstuff in Egypt. However, the country imports most of its production. The model opted for decreasing the cropped areas of faba beans throughout the study period. Hence, as it is assumed that the country would benefit if its production increases, the model can be examined under a scenario in which a policy constraint binds the model.

6. Conclusion and future work

To conclude, the aim of this study was to devise an integrated system of models allowing the optimisation of the crop mix to 2030 to lessen the impacts of climate change on the Egyptian agricultural sector, using different projection methodologies and validation techniques. Even though several aspects need ameliorations, the model offers a platform for decision-makers to assess policies and objectives and quantify their potential outcomes.

As temperatures would be increasing to 2030, most variables showed projected increases across the study period, viz. prices, costs, water consumptive use and cropping area. Hence, the model has proposed an optimal cropping pattern that would result in an increase in net revenue from $10.59 billion to $24.14 billion. The results of the optimal crop mix reflect the balance that the model aims to achieve, namely maximising the net revenue whilst using minimal water resources. This pattern is ensured by favouring all crops that generate high net returns and consume little water, followed by those that consume little water and generate average profitability, and then ones that use a lot of irrigation water and produce high net revenue. However, the model is always restricted by the issue of water scarcity and thus has to achieve a trade-off when favouring different crops. Furthermore, the addition of the self-sufficiency constraint resulted in an increase in wheat, along with several other crops. Yet net returns were decreased by 13.3%.

Several of the parameters and constraints of the models need to be enhanced. Because the increase in temperature during the study period and between the scenarios does not exceed 2% to 4%, the differences between the scenarios' results were observed to be minimal. Therefore, expanding the study period to reach beyond 2030 seems essential. Furthermore, including the agricultural seasons in Egypt in the model seems crucial. Accordingly, the intention is to run the model on a finer granularity on the regions' parameter. A rise in sea level is one of the main hazards of climate change facing Egypt due to its impacts on water inundation and salinisation and the rise in the ground water table. Therefore, one of our main goals is to include the effects of the increase in sea level. Furthermore, we intend to add crops such as fruit and palm dates.

References

Abdou A, 2003. Cropping structures adjustments under water limitations in the Egyptian agriculture. Paper read at the 14th International Farm Management Congress, 10–15 August, Perth, Western Australia.

Allen R, Pereira L, Raes D & Smith M, 1998. Crop evapotranspiration – Guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper No. 56, FAO, Rome.

Beynene T, Lettenmaier D & Kabat P, 2010. Hydrologic impacts of climate change on the Nile River Basin: Implications of the 2007 IPCC scenarios. Climatic Change 100(3-4): 433–61.

Brower C & Heibloem M, 1986. Irrigation water management: Irrigation water needs. FAO Corporate Document Repository, Training Manual No.3(3).

CAPMAS Yearbook, 2013. Annual statistical report for the cropping area and the agricultural production. Cairo: CAPMAS.

CGIAR, CCAFS, ILRI, CIAT, 2017. MarkSim DSSAT weather file generator. Available at http://gisweb.ciat.cgiar.org/MarkSimGCM/ (Accessed 19 April 2017].

Economic Affairs Sector, 2013. Agricultural Directorates of Governorates, Cairo: Ministry of Agriculture and Land Reclamation.

Eid HM, El-Marsafawy SM & Ouda SA, 2007. Assessing the economic impacts of climate change on agriculture in Egypt: A Ricardian approach. World Bank Policy Research Working Paper No. 4293, World Bank, Washington DC.

El-Gafy I, 2013. Integration among Egyptian governorates to optimize irrigation water use utilizing weight goal programming technique. Irrigation and Drainage 62(5): 559–77.

El-Gafy I, El-Ganzori A & Mohamed A, 2013. Decision support system to maximize economic value of irrigation water at the Egyptian governorates meanwhile reducing the national food gap. Water Science 27(54): 1–18.

El-Ramady HR, El-Marsafawy SM & Lewis LN, 2013. Sustainable agriculture and climate changes in Egypt. In Lichtfouse E (ed.), Sustainable agriculture reviews, vol. 12. Dordrecht: Springer.

FAO, 2006. CropWat. Available at http://www.fao.org/land-water/databases-and-software/cropwat/en/ (Accessed 6 July 2017).

FAO, 2017. FAOSTAT. Available at http://www.fao.org/faostat/en/#home (Accessed 4 April 2017).

Fischer G, Shah M, Tubiello F & Van Velhuizen H, 2005. Socio-economic and climate change impacts on agriculture: An integrated assessment, 1990-2080. Philosophical Transactions of the Royal Society B: Biological Sciences 360(1463): 2067–83.

IPCC, 2015. Climate Change 2014: Mitigation of climate change (Vol. 3). Cambridge: Cambridge University Press.

Madec G, Delecluse P, Imbard M & Levy C, 1997. OPA 8.1 Ocean General Circulation Model reference manual. Notes du pôle de modélisation, laboratoire d'océanographie dynamique et de climatologie. Institut Pierre Simon Laplace des sciences de l'environnement global, Saint-Aubin, France.

Mainuddin M, Gupta A & Onta P, 1997. Optimal crop planning model for an existing groundwater irrigation project in Thailand. Agricultural Water Management 33(1): 43–62.

O'Neill BC, Kriegler E, Riahi K, Ebi KL, Hallegatte S, Carter TR, Mathur R & Van Vuuren DP, 2014. A new scenario framework for climate change research: The concept of shared socioeconomic pathways. Climatic Change 122(3): 387–400.

McCarl BA, Musumba M, Smith JB, Kirshen P, Jones R, El-Ganzori A, Ali MA, Kotb M, El-Shinnawy I, El-Agizy M & Bayoumi M, 2015. Climate change vulnerability and adaptation strategies in Egypt's agricultural sector. Mitigation and Adaptation Strategies for Global Change 20(7): 1097–109.

Rosegrant M, Perez N, Pradesha A & Thomas T, 2016. The economy-wide impacts of climate change on Philippine agriculture. Policy Note 1, International Food Policy Research Institute (IFPRI), Washington DC.

Sarker R & Quaddus M, 2002. Modelling a nationwide crop planning problem using a multiple criteria decision making tool. Computers & Industrial Engineering 42(2): 541–53.

Sarker R & Ray T, 2009. An improved evolutionary algorithm for solving multi-objective crop planning models. Computers and Electronics in Agriculture 68(2): 191–99.

Sarker R, Talukdar S & Haque A, 1997. Determination of optimum crop mix for crop cultivation in Bangladesh. Applied Mathematical Modelling 21(10): 621–32.

Thomas TS, 2015. US maize data reveals adaptation to heat and water stress. IFPRI discussion paper 1485, International Food Policy Research Institute, Washington DC.

Van Vuuren DP, Edmonds J, Kainuma M, Riahi K, Thomson A, Hibbard K, Hurtt GC, Kram T, Krey V, Lamarque JF & Masui T, 2011. The representative concentration pathways: An overview. Climatic Change 109(1-2): 5.

World Bank, 2013. Climate change knowledge portal. Available at http://data.worldbank.org/topic/climate-change (Accessed 4 April 2017).

World Bank, 2017. World development indicators: Economic and social data services. Available at: http://data.worldbank.org/data-catalog/world-development-indicators (Accessed 17 May 2017).

Xie H, You L, Wielgosz B & Ringler C, 2014. Estimating the potential for expanding smallholder irrigation in Sub-Saharan Africa. Agricultural Water Management 131: 183–93.

Ye L, Tang H, Wu W, Yang P, Nelson GC, Mason-D'Croz D & Palazzo A, 2013. Chinese food security and climate change: Agriculture futures. Economics: The Open-Access, Open-Assessment E-Journal 8(2014-1): 1–39. http://dx.doi.org/10.5018/economics-ejournal.ja.2014-1