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Identifying agriculture land acquisitions for alleviating future food security concerns

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Abstract

The total available land for food, fuel, or forests is finite, while land demand is increasing and expected to increase further in the coming decades; resulting in deterioration of food security. Therefore, the corporate world adopted a solution of acquiring international agricultural land. Consequently, the global demand for land has progressively risen, but the question requiring decision support is - which lands to acquire for food production to ensure future food security? Food Science and Technology has vital pivotal roles to play in improving this situation, as food science is inherently multidisciplinary and motivated by the use of new technologies. In this paper, we endeavour to address this multidisciplinary food science question, by considering 16 Middle East North Africa (MENA) region countries having extreme economic diversity and enormous variation in adaptive capacity. Our study parameters consist of CO_2 fertilization, water scarcity and meta-parameter of climate change vulnerability. Using logical inference and principal of separate modifiability, major food security concerns were identified for 2030.

Keywords: food science; prediction; food security; decision support; Middle East North Africa.

Practical Application: Predicting food secure regions to provide decision support in identifying land acquisitions for food production.

1 Introduction

In 1798, Thomas Malthus (Malthus, 2017) challenged the utopian view by projecting that global population growth would inexorably overtake food production, and therefore, the humanity will have to endure the misery of hunger and starvation. However, as a consequence of better communal health processes, contemporary medication and treatment, the global population has swelled from an approximated 600 to 900 millions in 1750 AD to 7.5 billions today. Undeniably, usage of science and technology in agriculture, food and drink production has contradicted Malthu's prophecies and better food technologies actually contributed to global population growth. The mid-2008's, however, experienced a unique combination of food price hike and financial crises. The world began to saw acquisition of large expanses of agriculture land in the mostly poor, underdeveloped countries with crop-producing potential. The phenomenon of global land acquisition for food production is shown in Figure 1.

These agriculture land acquisitions were by governments and establishments of rich, food-insecure nations and private investors. In the target countries, land was comparatively economical to acquire, and the prospects to increase crop yields were mostly high. In recent years, the issue of large-scale, trans-national land purchases has soared towards the top of the sustainability agenda (Anseeuw et al., 2013).

1.1 Food science and food security

Food Science is inherently multi-disciplinary (Brigham Young University, 2017; Moraru et al., 2003) and is study of food and the application of corresponding knowledge thus acquired for the advancement of food products and processes, the conservation and storage of foods, and guaranteeing food quality and safety. With smaller number of farmers feeding an ever increasing world population, food must be suitably preserved and packaged for utilization often at a distant location and at a later time. Food scientists are engaged in all phases of this process i.e. starting from crop and animal and crop production until food consumption. This comprises developing novel and improved foods, investigating food for its safety and nutritive value, and exploring better ways to preserve food.

Food security critically contributes to the sustainability and economic growth of any nation. Regrettably, food insecurity has had an adversarial impact on population of world's developing countries, especially in the continents of Africa and Asia, most significantly for the Middle East North Africa (MENA) region. While food insecurity has adverse effects on many MENA region countries, the discipline of Food Science and Technology has fundamental functions in recuperating the conditions. The Food Scientists, Computer Scientists and Statisticians with cross-discipline background, can contribute by developing solutions, and application of proven technologies that might improve food security in developing countries; especially the MENA region.

In (Hastings, 2011) country-wise Food Security has been quantified and ranked in terms of six components, which are further divided into 21 finer parameters. Based on these parameters countries of the world have been assigned a current or prevalent food security rank. The lower the rank the better

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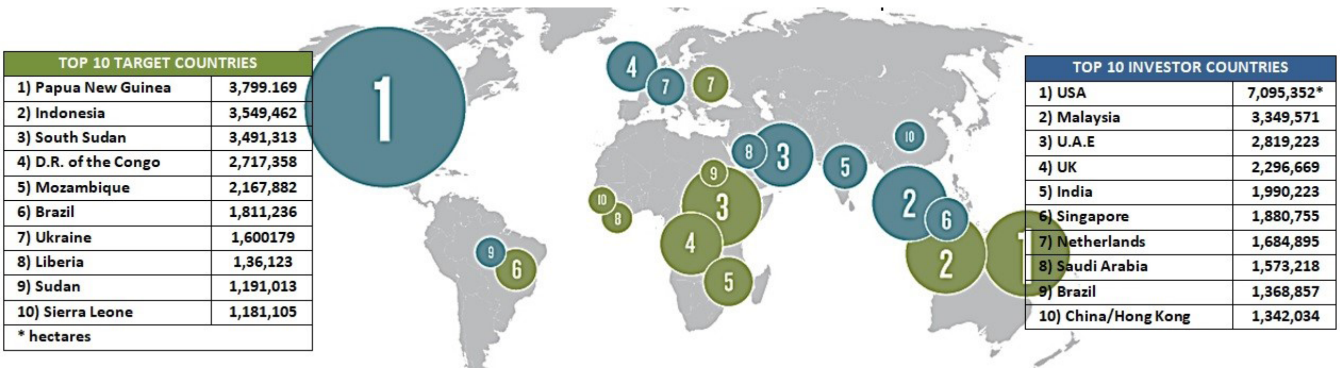

Figure 1. Buy or Sell? Top 10 investor and target countries for concluded transnational land deals, 2000-today (Harvey, 2014).

the food security. Our proposed solution uses the (Hastings, 2011) country-wise food security rank, along with the three parameters considered in this research. Our choice of the three parameters is mainly based on two criterion i.e. effectiveness of the parameters in reflecting food security (Steduto et al., 2012; Lal et al. 2005; Turral et al., 2011; Gerald et al. 2010; Harrigan, 2012) and availability of the corresponding data that can be extracted, transformed and cleansed. Subsequently, using logical inference and principles of separate modifibility (Sternberg, 2001, 2004) effective food security rank in 2030 is predicted for the MENA region countries considered.

1.2 Literature review

Large-scale land procurements have attracted considerable attention in the media, however, this phenomenon is usually difficult to measure because of the recent history of these land deals but also the deficiency of openness in many of the negotiations (Davis et al., 2015). Traditionally linear regression and integrated dynamic models have been used for incorporating socio-economic conditions into food security forecasts. Number of researchers have reported using linear regression to study food security w.r.t the relationship between the socio-economic and agro-meteoroloigcal parameters at sub-national (Gill & Khan, 2010) and household level (Gebre, 2012; Grobler, 2015; Mbukwa, 2013; Chatterjee et al., 2012). The benefit of these methods is the flexibility in allowing their customization as per available information resulting in their use in circumstances with comparatively restricted data sets, which is usually the case for underdeveloped countries with low or deteriorating food security.

The obvious limitation of linear regression is "forcing" linearity on naturally occurring non-linear relationships; while in the proposed solution non-linear relationships are considered (section-2.4). In (Foley et al., 1998) several limitations of coupling of dynamic models have been discussed. Simple dynamic models, frequently provide useful insights into the complex temporal relationships between variables. These models can also capture elusive feedback effects that are overlooked by statistical models. As dynamic models are required to be kept really simple, therefore, they may be so basic that more is lost than achieved (Evans, 2014), hence, the proposed solution uses empirical modelling i.e. data-centric mathematical models using accepted statistical techniques (section-2.5). Our proposed solution is centred around logical inference and principle of separate modifiability (Sternberg, 2001, 2004); more precisely inductive inference (Monti et al., 2009). The principle of separate modifiability is based on a type of independence i.e. if two processes are modules, then it should be conceivable to alter each process by exclusively altering the other. These assumptions are similar to Naïve Bayesian modelling, where attributes are considered to be independent, yet with this assumption there are several successful applications of Bayesian modelling (Peng et al., 2004).

2 Materials and methods

2.1 Countries considered

The Middle East and North Africa (MENA) is among the world's most diverse regions, with enormous variation in vulnerability to climate risks and adaptive capacity w.r.t the region's food security (World Bank, 2014). In view of the volume and diversity of data, it is not possible to collect, compile, process and analyse the related MENA region countries data and subsequently make projections for efficient decision support.

Therefore, to make the study manageable, we perform analysis using combination of three parameters and use bubble chart for short-listing the 16 MENA region countries to identify potential candidates for this study. The bubble chart results are shown in Figure 2 where selection of parameter based on (Hastings, 2011) ranking. From Fig-2 some clustering of the 16 MENA region countries (showed by dotted box) can be observed, with further overlapping of the bubbles within the cluster, such as Iraq-Mauritania so we consider one of them i.e. Iraq; overlapping of the bubbles for Yemen-Morocco so we consider one of them i.e. Yemen; statistical "closeness" of Egypt with Sudan so we consider one of them i.e. Egypt, overlapping of bubbles corresponding to Saudi Arabia-Oman so we consider one of them i.e. Saudi Arabia; closeness of Lebanon and Kuwait so we consider one of them i.e. Lebanon, thus covering 13 MENA region countries.

Among three countries not part of any cluster i.e. UAE, Israel and Jordan, we select one of them i.e. Jordan. Thus the MENA region countries short-listed for our study being, Egypt, Iraq, Jordan, Lebanon, Saudi Arabia and Yemen.

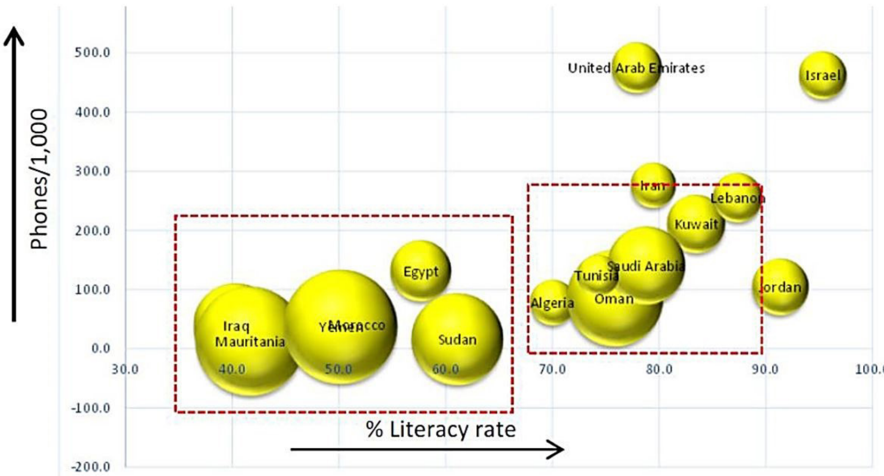

Figure 2. Bubble chart of 16 MENA countries with bubble diameter corresponding to birth rate.

2.2 Qualitative to quantitative transformation

The complexity of the food science and food security problem being considered increases because of the intrinsic heterogeneity of data, which is due to the multidisciplinary nature of the problem. For example, the data available for CO_2 fertilization and climatic change vulnerability considered in this study are usually qualitative, and thus allow qualitative classification, while water scarcity is quantitative.

Discrete qualitative data has hardly any order, and assignment of any numbers to groupings will be purely random. Because of the nonexistence of any order or identical periods, one cannot apply statistical (average, standard deviation) or arithmetic (*,-, +, /) or logical operations (=, >, <) on the nominal data. Thus, we need a process for allocating rank and order to the qualitative features, such as CO_2 fertilization and also develop numeric measures for climatic change vulnerability.

CO_2 fertilization

In (Fischer, 2009) it was predicted that the impact of CO_2 fertilization on adopted crops could result in 8% decrease in cereal production in Middle-East resulting in deterioration of food security, while an increase of 14 to 19% in cereal production in Central. The CO_2 fertilization prediction results are of no direct utility for our work; because of macro level of detail at the regional rather than at a micro level, which is the focus of our work.

CO_2 fertilization is a key parameter used in this study and, like all parameters, quantitative value is required at the country level. In (Mintz, 2013) the impact of CO_2 fertilization is given in the form of a thematic color-coded map and but cannot be used directly in a statistical model at the country level. To calculate the mean value of CO_2 fertilization for each of the six shortlisted MENA region countries considered, the most suitable method using Mauna Loa data (Tans & Keeling, 2015). However, this method is not within the scope of our work.

Instead, online image processing of the regional thematic map raster data is done to determine percentage change in foliage cover from 1982-2010. For this purpose, *Image Color Summarizer* (Krzywinski, 2017) with the RGB color model is used. For the period considered, no decline was observed in leaf production for the MENA region countries considered, therefore, Red and Green colours in the image (Fischer, 2009) are used to create Yellow colour conforming to 0-10% CO_2 fertilization. Finally, taking the weighted average of Yellow, Green and Blue pixel (P) values (as Red was not there) for a country and combining as per Equation 1 the weighted average CO_2 fertilization (μ_{CDF}) for a country is defined as:

$$\mu_{CDF} = \left(\frac{W_G \times P_G + W_B \times P_B + W_Y \times P_Y}{140} \right) \times 30 \tag{1}$$

In Equation 1 the multiplicative weight W_i for the i^{th} color is assigned as per the colour legend values of the schematic map. For example, Yellow is shown in the map to be between 0 and 10, therefore, $W_Y = -0.1$, similarly $W_G = 0.15$ and $W_B = 0.8$. Subsequently, cumulative normalization is done with respect to 140. The reason being, using RGB model, making all colours equal to 140 results in a grey shade, which incidentally is also the colour in the CO_2 fertilization thematic map for unavailable data. The normalized weighted sum of the pixels in Equation 1 is multiplied with 30 so as to bring the results as per CO_2 fertilization thematic map legend values. The transformed qualitative to quantitative results for CO_2 fertilization are given in Table 1.

Climatic-change vulnerability

Globally, about 50 countries are predicated to be acutely susceptible in 2030 to climate change impacts (McKinnon et al., 2010). In (McKinnon et al., 2010) pre-existing traits of society were covered and identified to be altered by climate change and then mapped to corresponding vulnerability level. The probable climate change (meta-parameter) effects were analysed and four major socio-economic factors identified for consideration are as follows:

Table 1. CO2 fertilization color-coded data of thematic map (Mintz, 2013) converted into CO_2 fertilization percentages.

Country	Avg[R]	Avg[G]	Avg[B]	Avg[Y]	μ_{CDF}
Egypt	201	202	196	201.5	35.77
Iraq	192	209	176	200.5	32.59
Jordan	224	225	220	224.5	40.13
Lebanon	171	209	134	190	25.61
Saudi Arabia	211	213	210	212	38.30
Yemen	200	212	187	206	34.45

Avg[R], Average of Red thematic colour; Avg[G], Average of Green thematic colour; Avg[B], Average of Blue thematic colour; Avg[Y], Average of Yellow thematic colour created from red and green thematic colours.

i) **Health Impact (HI):** Climate change sensitive diseases, such as malaria, dengue fever, and cholera may cause more deaths;

ii) **Weather Disasters (WD):** Weather changes resulting damaging storms, wildfire and floods may cause more deaths;

iii) **Habitat Loss (HL):** Mounting sea-level, decrease of arid/dryland may cause loss of human habitation and

iv) **Economic Stress (ES):** Loss of agricultural land may result in shortfall of environmental resources, which may cause financial loss. The effect of these four factors were represented qualitatively by color-codes (McKinnon et al., 2010), which we convert into quantitative values extending from 1 to 11 i.e. Acute (11), Severe, High (with finer progression of increase and decrease) followed by Moderate and Low (1). The average percentage of the qualitative estimates was later considered for each country as per Equation 2.

$$\mu_{CCV} = \frac{HI + WD + HL + ES}{4 \times V\max} \times 100 \tag{2}$$

Note that in Equation 2 the denominator Vmax is the maximum value of any CCV parameter which is 11.

2.3 Water scarcity

As per (White, 2013), water scarcity (WS) is recognized to be lacking access to acceptable quantities of water for human and environmental uses. This is increasingly being accepted in many countries as a grave and growing problem. Lately, 166 million in 18 countries are experiencing water scarcity, while almost 270 million more in further 11 countries are considered water stressed (Gardner-Outlaw & Engelman, 1997). Water scarcity is already a quantitative measure and can be used directly. In this paper, moderate water scarcity projections are considered based on (Gardner-Outlaw & Engelman, 1997).

2.4 Formalism for inference (Sternberg, 2001)

In this section, we provide the formalism for combining the parameters for logical inference. The section is based on the terminology and taxonomy (Sternberg, 2001) that unifies and relates diverse approaches for module identification. We proceed by asking the question, *How a complex process can be split into meaningful parts, or ``modules"?* And we also consider a general standard for describing the modules of a complex process. The principle is of separate modifiability, which is a type of independence i.e. if two processes are modules, then it should be conceivable to alter each process by exclusively altering the other, such as CO_2 fertilization and climate change vulnerability.

Assume a process is theorized to comprise of two modules **A** and **B** with matching theorized pure measures M_A and M_B. They are "pure" in the context of being selective: for example, M_A should not differ with changes in **B**. Examples of measures of a process include its interval, and in our case the amount of activity in certain geographic regions, such as precipitation.

Suppose we have one measure M_{AB} that duplicates a characteristic of the complete complex process of interest i.e. a process that comprises of component processes **A** and **B**. Meaning, we only know the *combined* impacts of **A** and **B** to a measure M_{AB} that is be contingent on both of them. To perform inferences from the data, we must be aware or theorize how the impacts of **A** and **B** collectively influence M_{AB}. In this paper we will consider mainly two combination rules i.e. *summation* and *multiplication* (hybrid rules are also possible).

Summation can occur as the combination rule if processes **A** and **B** are linearly organized as *stages* i.e. functionally dissimilar operations that happen during non-overlapping periods, and such that the response happens when both operations have concluded. Under the current analysis, we have used this methodology for measuring climatic change vulnerability.

Suppose we either know or theorize that the combination rule is instead *multiplication*: the combined input of processes A and B is the product of their separate inputs, or $M_{AB} = u_A \times v_B$. If factors F and G selectively effect A and B, respectively, then we have

$$M_{AB}(F_j, G_K) = u(F_j) \times v(G_k) \tag{3}$$

In Equation 3 u(Fj) is a function that defines the relationship between level of F and the contribution of **A** to M_{AB}.

Generally, the separate modifiability of modules prevents one influencing the other. Thus in the case of multiplicative combination rule, an additional hypothesis is required i.e. we must assume that the contributions from **A** and **B** to M_{AB} have zero correlation.

2.5 Parameter selection

Using the available food security ranking (Hastings, 2011) we propose to use the multiplicative combination rule for inference, and assume the three parameters i.e. WS, CCV and CDF to be uncorrelated. As discussed, water scarcity (WS) and climate change vulnerability (CCV) have an overall negative impact on food security (Steduto et al., 2012; Lal et al., 2005; Turral et al., 2011) while CO_2 fertilization (CDF) has a likely possitive impact depending on the species and environmental conditions (Reddy, 2015; McGrath & Lobell, 2013; Lobell & Burke, 2009). Therefore, based on combination by multiplicative rule as per Equation 3 we define the Effective food security Average Rank as follows.

Let the food security rank be denoted by $R\ (p_1, p_2, p_3 \ldots p_n)$ *i.e.* R is a function of number of parameters as already discussed. The parameters that we have considered are WS, CCV and CDF. The predicted food security rank R^P is defined as

$$\Re^P = \frac{\Re \times \left(\left(\psi_{WS} \times \mu_{WS} \right) \left(\psi_{CCV} \times \mu_{CCV} \right) \right)}{\psi_{CDF} \times \mu_{CDF}} \quad (4)$$

In Equation 4 ψ_i is the weight assigned to the i^{TH} parameter considered. There could different criterion of assigning weights to the parameters considered, the proposed approach is to assign a weight based on the importance of that parameter i.e. how much statistically discriminating that parameter is, therefore, we consider standard deviation (SD or σ). A small standard deviation is suggestive of the closeness of the data points to the mean (or the expected value) of the set, whereas a high standard deviation is suggestive of the spreading of the data points across a wider range of values. Let σ_i be the standard deviation of the i^{TH} parameter here i being either of WS, CCV or CDF and μ be the mean of the standard deviations of these parameters, then the normalized weight ψ_n (or normalized standard deviation) is calculated as follows:

$$\mu_m = \frac{1}{n} \sum_{i=1}^{n} \left(ó_i - \mu \right)^2 \quad (5)$$

$$\psi_n = \left(\frac{\sigma_i - \mu}{\sqrt{\mu_m}} \right)^2 \quad (6)$$

Note that multiplier based adjustment of R proposed in Equation 6 is similar to the foresight scenario adjustment for year 2080 as discussed in (Thorne et al., 2007) which takes into consideration future losses, including agriculture impacts. The 2030 food security results for the shortlisted six MENA region countries calculated as per Equation 5 through 6 are shown in Table 2.

3 Results and discussion

Figure 3 is generated using the collective results of Equations 1, 2 and water scarcity statistics (Gardner-Outlaw & Engelman, 1997). Figure 3 shows the 2030 expected values calculated as percentages for the factors/parameters considered in this study i.e. water scarcity (Gardner-Outlaw & Engelman, 1997) CO_2 fertilization (Fischer, 2009; Mintz, 2013) and the climate change vulnerability meta parameter (McKinnon et al., 2010) for the six MENA region countries. Using R and based on Equations 5 through 6, R^P is calculated, with the results shown in Table 2.

From Table 2, it can be observed that for the six MENA region countries considered, three countries are predicted to have a decline in their food security rank in 2030, with the most effected being Yemen. Three countries are predicted to have positive improvement in their food security rank for 2030, with the greatest improvement being for Lebanon. However, agriculture plays a minor role in Lebanon's economy i.e. contributes only 5% and 8% labour force employed in farming (Food and Agriculture Organization, 2017a). The second country with improved predicted food security rank being Saudi Arabia, which is already pursuing overseas agriculture land acquisitions (Al-Obaid, 2010) in view of depletion of local ground water reserves which were used to irrigate wheat production.

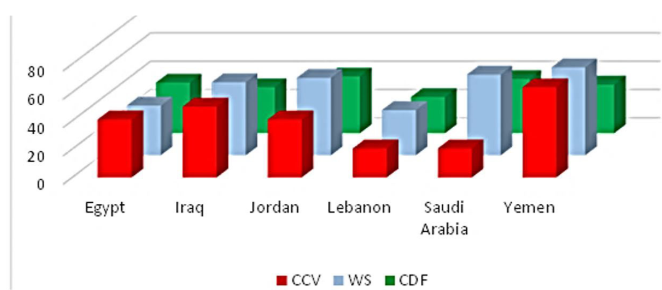

Figure 3. Comparison of six MENA region countries for the percentage values of three parameters considered in 2030. CCV: climate change vulnerability; WS: water scarcity; CDF: CO_2 fertilization.

Table 2. Predicted Food Security Rank results.

Country	Climate vulnerability	Water Scarcity	CO_2 fertilization	FS rank 2015	FS rank 2030	% change
Egypt	40.91	35.15	35.78	111	100.59	9.38
Iraq	50	51.69	32.59	145	259.22	-78.77
Jordan	40.91	54.72	40.14	122	153.41	-25.74
Lebanon	20.45	31.98	25.62	164	94.39	42.45
Saudi Arabia	20.45	57.03	38.30	106	72.76	31.36
Yemen	63.64	62.14	34.36	186	481.25	-158.74
(SD) σ	16.868329	12.3152	5.11			

FS, Food Security; SD, Standard Deviation.

Due to acute shortage of ground water, the Kingdom completely terminated its wheat cultivation by the end of the 2015/16 marketing year (Food and Agriculture Organization, 2017b). Finally, the Egyptian economy has depended heavily on its agricultural sector for food, fibre, feed and other products. Egyptian agriculture provides living to about 55% and employs 30% of the labour force, contributes roughly 17% of the GDP and 20% of all foreign exchange earnings (El-Nahrawy, 2017). Thus among the countries with positive improvement in food security rank in 2030, Egypt seems to be the only viable choice for overseas agriculture land acquisition.

Our results corroborate with the results of IFPRI (International Food Policy Research Institute) IMPACT (International Model for Policy Analysis of Agricultural Commodities and Trade) model (Rosegrant et al., 2008) and the FAO Food Balance Model (Food and Agriculture Organization, 2008). Both models predict that demand for food in the Arab world will significantly increase by 2030 to the level, such that the local food production will be unable to keep pace, resulting in increased reliance on food imports.

4 Conclusions

Predicting food security is a data-intensive and complex task, especially because of intricate micro and macro relationships. In this paper, using logical inference and principle of separate modifiability, we have predicted food security of six MENA region countries (Saudi Arabia, Egypt, Jordan, Iraq, Lebanon and Yemen) for 2030 so as to facilitate decision making in agriculture land acquisition; the proposed methodology can be used for other countries too. However, the challenge being the heterogeneity of the available data, with diversity of type, scale and distribution across diverse sources. Our study identified major food security concerns in 2030 for three MENA region countries and identified Egypt as a possible attractive option for international agricultural land acquisition by food insecure countries.

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