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The vulnerabilities of agricultural land and food production to future water scarcity

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ABSTRACT

Rapidly increasing populations coupled with increased food demand requires either an expansion of agricultural land or sufficient production gains from current resources. However, in a changing world, reduced water availability might undermine improvements in crop and grass productivity and may disproportionately affect different parts of the world. Using multi-model studies, the potential trends, risks and uncertainties to land use and land availability that may arise from reductions in water availability are examined here. In addition, the impacts of different policy interventions on pressures from emerging risks are examined.

Results indicate that globally, approximately 11% and 10% of current crop- and grass-lands could be vulnerable to reduction in water availability and may lose some productive capacity, with Africa and the Middle East, China, Europe and Asia particularly at risk. While uncertainties remain, reduction in agricultural land area associated with dietary changes (reduction of food waste and decreased meat consumption) offers the greatest buffer against land loss and food insecurity.

1. Introduction

With a rapidly expanding population and changing climate, pressures on food production systems are expected to increase in the coming decades. To meet current demand, it is estimated that over one third of the earth's land surface is used as cropland or pastures (FAO, 2018a). Although management intensification, such as better genetics, increasing fertiliser application rates (FAO, 2018b), and better-fed livestock (Herrero et al., 2013), has led to more productive systems, some of these gains are at the expense of the environment, including increasing greenhouse gas (GHG) emissions. Although closing crop yield gaps has been proposed as a way of alleviating pressures on food production systems (Foley et al., 2011; Mueller et al., 2012a), the net benefits of these strategies are predicated on environments that are not resource limited, particularly through the availability of water.

Agriculture is the largest consumer of water, where the irrigation of croplands accounts for 70% of water withdrawals (McDaniel et al., 2017). Despite 95% of agricultural land being primarily rainfed

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(Hadebe et al., 2016), declining water availability / increasing water scarcity can have a negative impact on cropland and pasture productivity. For example, a failure to meet the water requirements of crops has led to decreasing yields of staple crops such as maize in China (Meng et al., 2017). However, to maximise crop yields, Davis et al (2017) found that it would require a 146% increase in global irrigation water use. Furthermore, Matiu et al (2017) demonstrated that consecutive years with warm and dry weather ("climate intensification"), reduced yields of some crops, including maize and wheat. With regards to pasture lands the correlation between productivity rates and precipitation variability (intra and inter annual) is high, particularly in regions such as Sub- Sharan Africa (Sloat et al., 2018). Therefore, future changes in water availability have the capacity to restrain livestock production expansion or even hinder maintaining ongoing production (Sloat et al., 2018).

Modelling studies, particularly multi- model ensembles, offer the opportunity to understand the risks, uncertainties and spatial differences changes in agricultural land and water availability may have on food production into the future. Using a global hydrological model coupled to a water resources model (Arnell et al., 2011; Gosling et al., 2010), climate change patterns from 21 different global circulation models (GCMs) were analysed to provide an index of water scarcity for each of the global watersheds. While differences exist between the different model simulations, in terms of their projected changes, under some scenarios there could be a doubling in the number of people exposed to water scarcity by the year 2050 (Gosling and Arnell, 2016). Across all models, increasing global temperatures was the principal driver of changes in the water scarcity index. Although projections for some of the watersheds indicated that there could be an increase in runoff, exposure to water scarcity is expected to be particularly pronounced in North Africa and South East Asia.

Studies using models such as GLOBIOM and IMAGE (Havlik et al., 2014; Stehfest et al., 2014) provide estimates of the extent of cropland and pasture that are required to feed national and global populations in the future, under different shared socio-economic pathways (SSPs). By balancing trade, food demand and production in line with population projections, the land required to feed a population is calculated, and is particularly sensitive to productivity. However, model projections like these extrapolate the land requirements of a country or region based on the current location of managed land, its extent and productivity, but typically changes in the availability of water and in some cases, diet are not explicitly considered. Therefore, by assuming that land is always available for agricultural use and able to achieve required yields (through, for example, improved irrigation efficiencies), projections may overestimate the amount of agricultural land available and its productivity.

The aim of this study, therefore, is to combine the projections of changes in water scarcity, defined in Arnell et al. (2011) as the ratio between water withdrawals and resources with the projected areas of future agricultural land, to identify the potential regional vulnerabilities of agricultural land and food production to water scarcity. By combining global maps of projected cropland and pasture area with an ensemble of water scarcity projections, we aim to quantify the risks that water scarcity could pose to land-based food production in 2050. An in-depth analysis is also undertaken for specific food commodities that represent a significant proportion of global food products to demonstrate the commodity-specific variation to potential risks: maize, rice, wheat, as these represent a significant proportion of global proportion of crop productivity, vegetables, fruit and pulses on croplands, and cattle production systems on grasslands.

Finally, by comparing multi model estimates of the change in land requirements under different future scenarios, including the SSPs and a subset of scenarios specifically targeting food security (hereinafter referred to as "Food Secure" scenarios), we examine how different policy pathways can help reduce, or increase, exposure of countries and regions to the potential loss of food production in 2050 due to water scarcity.

2. Datasets and methods

2.1. Global data sources

Outputs from 21 different general circulation models / global climate models (GCMs) were combined with a hydrological model to estimate the percentage change in annual runoff relative to the 30-year average from a "climate normal" reference period, i.e.1960 – 1990. This time - period was selected as the baseline as it was consistent with that used in the creation of the climate change data used in the original GCM model simulations. Using these model outputs, the water scarcity index in 2050 was calculated for the 1339 global watersheds (Arnell et al., 2011). The projections reported by Arnell et al. (2011) were for three shared socioeconomic pathways (SSPs), combined with 4 representative concentration pathways (RCPs) as represented by 21 GCMs. Arnell et al (2011) reported that uncertainty in modelled projections was greater between the different GCMs than between the scenarios investigated particularly on a regional scale. Model selection is important in ensuring that differences in projections are accurately represented (Gosling and Arnell, 2016), particularly on a regional basis. However, in the absence of suitable metrics that could reasonably be applied here to select the most "appropriate" GCM, for this study 5 GCMs we selected at random. This ensured that an ensemble approach was maintained but avoids user defined bias in the subsequent data analysis. Therefore, projections on water scarcity from the SSP 2 scenario from the 5 GCM models: Commonwealth Scientific and Industrial Research model (CSIRO_Mk3), Hadley Centre Global Environment Model (HADGEM), Institute for Numerical Mathematics Climate Model (INMCM4), Institute Pierre Simon Laplace (IPSML_MR), Model for Interdisciplinary Research on Climate (MRIOC_CM3), were used.

Maps of cropland, pasture, vegetable, fruit and pulse areas (hectares, ha) were sourced from (Monfreda et al., 2008; Ramankutty et al., 2008). All data sets were created based on a mixture of satellite derived data mixed with national, state and country census statistics, and were expressed on a global 5 arc-minute grid. For animal production systems, estimates of biomass consumption of each livestock type is detailed in Herrero et al (2013); globally disaggregated estimates of grass consumption (Mt) associated with cattle milk and meat production, are also presented on global 5 arc-minute grid (Herrero et al., 2013). In both instances, the datasets pertain to the year 2000 and were used in this analysis due to their spatial extent and specificity in spatially disaggregating different crop and livestock systems.

2.2. Future land use under the shared socioeconomic pathways (SSP)

Future land cover projections for cropland and pastures, as simulated by a range of different models, were sourced from Alexander et al. (2017). Model simulations encompassed several socio-economic scenarios that included simulations for adoption of biofuels, changes in afforestation and taxation policy. For this study, only land cover projections based on three core SSPs: SSP1 (sustainable pathway), 2 (business as usual/middle of the road) and 3 (rocky road/unsustainable), were selected (Table 1). To this, additional scenarios were added from the FALAFEL model (Powell, 2015) and from the Bajzelj et al. (2014) study, since these studies focussed specifically on food security scenarios, hereafter termed "Food Secure" scenarios. Food secure scenarios simulated by Bajzelj et al. (2014) focus on the closing of yield gaps, reduction in food and agricultural waste by 50% and a transition to healthy diets. In the FALAFEL model (Powell, 2015) Food Secure scenarios are based (i) livestock product consumption, as a percentage of the total diet, not increasing beyond 2020 and (ii) livestock production intensification and conversion efficiencies increasing to bring them close to western averages (Table 1). Each model simulates land cover at different temporal and spatial scales. Therefore, to enable

Table 1

Details of the land projections models used as part in the model inter-comparison.

Model name	Spatial resolution	Model type	Scenarios Simulated	Time scales	Reference
AIM	Global model – disaggregated to regional units	Computable general equilibrium model	SSP 1,2,3	Decadal to 2010	Fujimori et al., 2010
Falafel	Global	Rule-based	Food Secure pathways	Decadal to 2050	Powell, 2015
FARM	Global model – disaggregated to regional units	Computable general equilibrium model	SSP 1,2,3	Decadal to 2050	Sands et al., 2014, 2017
GCAM	Global model – disaggregated to regional units	Partial equilibrium model	SSP 1,2,3	5-year intervals to 2010	Calvin et al., 2013
GLOBIOM	Global – spatially disaggregated on 5 arc resolution	Partial equilibrium model	SSP 1,2,3	Decadal to 2100	Havlik et al., 2014
IMAGE	Global – spatially disaggregated on 5 arc resolution	Land use and development model	SSP 1,2,3	Decadal to 2050, then 2100	Stehfest et al., 2014
Magnet	Global model – disaggregated to regional units	Computable general equilibrium model	SSP 1,2,3	Decadal to 2050	van Meijl et al., 2006
Bajzelj	Global model – disaggregated to regional units	Empirical model of global land systems	Food Secure pathways	5-year intervals to 2050	Bajzelj et al., 2014

direct comparisons, the total land area under cropland and pasture for two time periods 2010 and 2050 were selected. Land cover was then scaled to the finest possible resolution available across all models which was; Global, Africa and the Middle East, South and Central America, Brazil, USA, Canada, Europe, Asia, India, China, Oceania and Russia.

Changes in the agricultural area due to the impact a policy pathway, (SSP 1,3 and Food Secure) in 2050 relative to the corresponding modelled baseline or SSP2 was calculated. By fitting smoothed regression lines with 95% confidence intervals (in the R statistical package), trends from the year 2010 to 2050 were then extracted both globally and regionally. This allows patterns and the uncertainty in model outputs to be examined temporally, spatially (global, regional) and for each scenario.

2.3. Data aggregation, analysis and impact assessment

To calculate the extent of current agricultural land that could be vulnerable to changes in water availability, spatial overlays (in ArcGIS) between global maps that contain (i) the percent change in water runoff and water scarcity estimates in 2050 (from each of the 5 GCMs), and (ii) global maps of the current extents of cropland and pasture area were made. From this, vulnerable land was calculated on a country level as the percentage of the total area in each country that is in a watershed defined as water scarce and with annual water runoff that is declining relative to a long -term baseline. Values were then aggregated to a regional level, so that the percentage of agricultural land at the same spatial resolution as the SSP datasets (Section 2.2) could be calculated. This was then repeated with global maps of specific commodities, such as wheat and rice among others (Fig. 1), to provide an understanding of the types agricultural systems most at risk.

Projections of agricultural land in 2050, under different SSPs and Food Secure scenarios were sourced from models of varying complexity (Table 1) and spatial resolution. In each instance, the total agricultural area (pasture + cropland) and population, in each the region, 2010 and 2050 was calculated. From this, the number of people fed per hectare of land, in 2050, was calculated from the regional agricultural area and population. The metric “people no longer fed” is calculated from the total agricultural land and population within a region, and provides an assessment of changes to food insecurity in relation to production vulnerability. A detailed description of how it is calculated is given in S.I.c. Although this is a simple metric describing the dependency of regional populations on production from the regional agricultural land and does not explicitly consider trade and nutrient supply. Domestic and food supply of agricultural commodities within a region is strongly correlated to agricultural production within the region (Figure S.I.1a,b) and therefore the creation of this relationship allows the potential consequences a loss of agricultural land on future populations to be examined, as defined by each model and scenario.

The reduction in regional agricultural land, in each model and scenario (Table 1) was based on the percentage of land classified as being vulnerable to water scarcity as described previously. More specifically, for each region, the percentage of agricultural land defined a vulnerable, averaged across each of the 5 GCM model outputs, was multiplied by the corresponding regional areas projected in 2050. All productivity from this subset of land was then assumed to be lost. Finally, using the metric of people fed per hectare, the number of people that potentially could no longer be fed due to loss of this land was calculated on a regional basis. However, it is important to note that in some instances, particularly in the Food Secure pathways, modelled agricultural areas in 2050 decreased relative 2010.To account for this, the percentage reduction in agricultural area between 2010 and 2050 was estimated for each model in Table 1. In each region when the percentage reduction in agricultural area between 2010 and 2050 was greater than the percentage of vulnerable land, it was assumed that no land could be classified as vulnerable. Conversely, if the percentage of vulnerable land was greater than the reduction in total agricultural

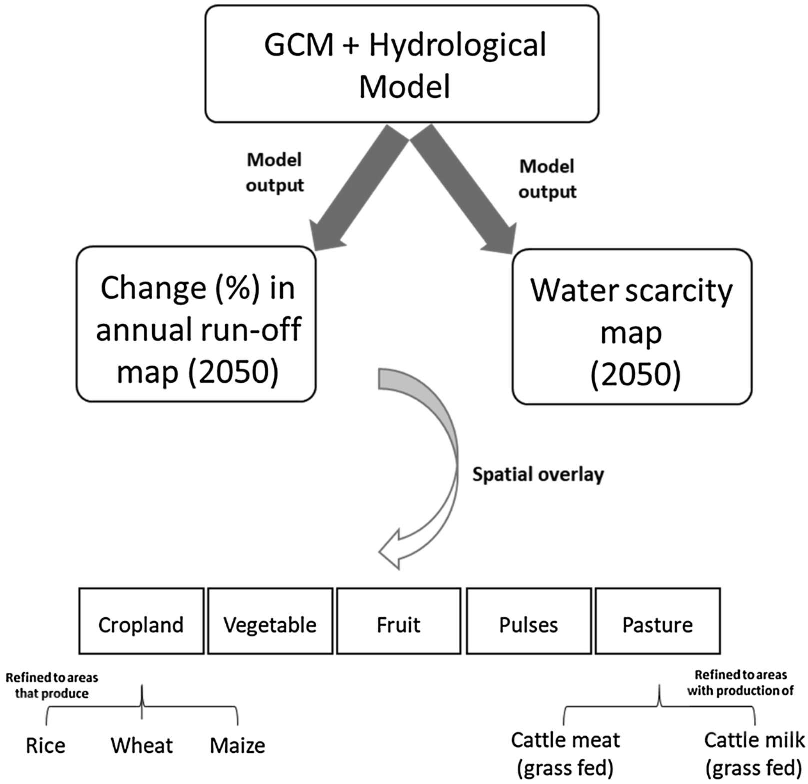

Fig. 1. Schematic representation of the spatial overlays and data analysis performed using outputs of a hydrological model driven by five global circulation models (GCM), a range of global land use projections from different land use change models and data on the areas used to produce a range of agricultural commodities.

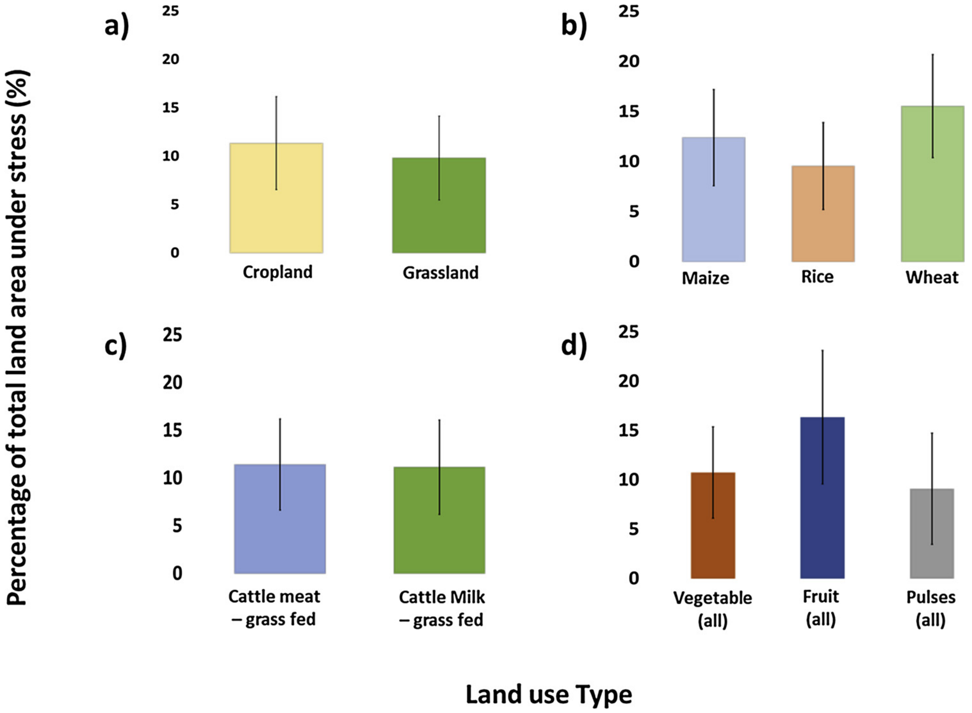

Fig. 2. Percentage (%) of the total global area of land that is classified as vulnerable for (a) croplands and pasture land and (b) land used in the production of maize, rice and wheat, c) region in which cattle products; milk and meat, that is primarily classified as grazing systems are produced, d) land used in the production of vegetables, fruit and pulses. The columns represent the average values using outputs from the 5 GCM models used to drive the hydrological model, and bars represent the standard error in the range of values.

area, land availability was reduced by the difference between the two estimates. For example, if in Europe 20% of all agricultural land was identified as vulnerable and modelled outputs for an SSP indicates that there was a 5% reduction in the total agricultural area between 2010 and 2050, only 15% of the total agricultural area was assumed to be vulnerable.

Specific details on model assumptions, step by step equations and regional classifications are detailed in the supplementary information.

While trade gives the opportunity to compensate for losses in different agricultural commodities, the quantity of different products available for trade is also sensitive to losses in the productive capacity of a country. Trading information from each model in Table 1 was not available for this analysis. However, using statistics on the long-term trading patterns of specific commodities within and between regions allows for an understanding of how loss of agricultural land may disrupt the trade flows of specific agricultural commodities between traditional trading partners if current interactions are maintained. Long term statistics on the export quantities of trade of the different agricultural products; wheat, rice, maize, cattle milk and meat, vegetables (all), fruit (all), pulses (all) from FAOSTAT (2018) were used. For each country and region, the total quantity of exports was calculated regionally as was the contribution of each commodity to the total. Finally guiding statistics on other economic indicators, as well as current estimates of water withdrawals were also scaled on a regional basis. This helps to understand the difference in the economic importance of agriculture across different regions in the world that may also be affected by loss of production.

3. Results

3.1. The vulnerability of land to water scarcity and changing baselines

The multiple model projections of baseline changes and water scarcity combined with land cover maps indicate that approximately 11% (+/- 5%) of the global croplands and 10% (+/- 5%) of the global pasture area may be vulnerable to water scarcity because of climate change (Fig. 2). Similar results were also found for the land growing specific commodities: maize, wheat, rice, vegetables (all), fruit (all) and pulses (all). For these land uses, the percentage of the total land that could be classed as vulnerable ranged between 9 and 16% (Fig. 2). Globally, of the total grass biomass consumed by cattle for milk and meat production, 11% is consumed in regions subject to reduced water availability in the future. In all instances, differences between the GCM projections drive uncertainty, which was around 5% (standard deviation) for each commodity assessed.

The percentage (%) of the total area classified as vulnerable varies quite significantly between regions for cropland and pasture area, and for land producing specific commodities. In regions such as Oceania, Canada and Brazil only approximately 1% of all agricultural land was found to be vulnerable to water scarcity, since agriculture is already largely absent in the areas of declining run-off or water scarcity (S.I.2a, b, c and d). Conversely in Europe, China, and Africa and the Middle East, a significant proportion of crop and pasture land is classified as vulnerable in 2050 (S.I.2a–d), but with an uncertainty higher (~10%) than the global uncertainty. In Europe, the vulnerable area was found to be 20% of crop and 16% of pasture land; in China, 20% of cropland and 13% of pasture land and in Africa and the Middle East, 30% of cropland and 13% of pasture land. For most commodities, estimates of the vulnerable area were broadly similar (S.1c and d), though significant differences were found for some, particularly wheat (Figure S.1b). In Europe and China, between 20 and 25% of land used for wheat production is deemed vulnerable, but in Africa and the Middle East, when averaged across the 5 GCM models, 50% of land used to produce wheat is vulnerable.

Declining water availability can impact the production of animal products, such as milk and meat, particularly those reliant on grazing. In each of three regions; Europe, China and Africa and the Middle East; approximately 20% (between 19 and 23%) of the biomass consumed by cattle to produce milk and meat is in areas vulnerable to changes in water availability due to climate change (Figure S.1c).

3.2. Future land demands under different SSPs

The change in the total land area (cropland and pasture) under the SSP (1 and 3) and Food Secure scenarios from 2010 to 2050 across all models was calculated (Fig. 3). The change in area relative to the corresponding baseline (SSP2 or equivalent); Fig. 3) is very different among scenarios. Modelled outputs were available on a global basis for all scenarios (including the Food Secure scenarios) but were available regionally only for SSP 1 and 3.

Globally, model projections under SSP1 (and even more pronounced in the Food Secure scenarios) suggest there should be a decrease in total agricultural area between 2010 and 2050, as improvements in technology, a slowing rate of population increase and reduction in waste and dietary change take effect (Fig. 3). Conversely, model projections for SSP3 suggest that more land will be required to feed a rapidly increasing population, relative to the baseline even from 2010. The influence that each SSP has on future agricultural land requirements is also broadly replicated on a regional basis (Fig. 3). In Europe, however, contrary to other regions, model projections indicate that there could be a decline in area under SSP3, though the difference in area between SSP2 and SSP3 is relatively small and is the result of divergent projections (some models project an increase and others a decrease in agricultural area). Total cropland area declines globally and across regions for SSP1 and Food Secure scenarios and increases for SSP3 (S.I.2a) with good agreement across models. There is greater uncertainty for projections of grassland extent in 2050 (S.I.2b), particularly in Africa and the Middle East, and the Americas.

3.3. Food security risks of declining land availability

Uncertainty in the vulnerability of current agricultural land, due in part to uncertainty in GCM predictions as detailed in Section 2.1, has implications for food security, particularly since agricultural expansion tends to be centred around the current location of agricultural land. As detailed in Section 2.3, estimating the number of people fed per hectare of land in each region as estimated by each model in 2050 provides information on the potential risks to regional populations if the regionally specific fractions of land defined as vulnerable can no longer be used for agricultural production. Moreover, the relationship also allows us to understand how policy interventions such as choosing more sustainable pathways or dietary changes can mitigate against productivity losses. For each of the four pathways, the total agricultural land area predicted by each land model in 2050, was reduced by increasing quantities based on the methodology described in Section 3.1. The gap, or number of people theoretically no longer fed from this reduction in available land was estimated both globally and regionally (Fig. 4).

In both the SSP2 and SSP3 futures, the agricultural land area, from 2010, is expected to increase due to an increasing population. Consequently, any loss of agricultural land will instantly have an impact on food security (Fig. 4a). The greatest share of the population affected in both SSP2 and SSP3 occurs in African and Middle Eastern countries (Fig. 4b), which is unsurprising due to the rapid population growth expected in this region, combined with reduction in water availability. More specifically, if all vulnerable land was unproductive, this translates into 6% of the total population of African and Middle Eastern countries in both SSP2 and SSP3 being affected. Under SSP3, which envisages a “rocky road” future, when averaged across all models, 178 million people would be no longer fed due to the combined effects of increasing population and lost production on land vulnerable to water scarcity. China and Europe account for between 9 and 11% of the global population no longer fed respectively, with the value depending on the SSP. In both cases, this translates to between 4 and 6% of their respective populations, although in terms of absolute numbers, a larger number of people (~50 million) are affected in China.

Conversely, under SSP1 (sustainable) and Food Secure (waste reduction, dietary change) scenarios, the modelled contraction in agricultural land acts as a buffer to potential losses due to water scarcity, although the extent depends on the future scenario. For example, under SSP1, efficiency gains in agricultural production means that the corresponding reduction in land (S.I 2 a, b) can compensate for land losses. However, parity between the two counter balances is achieved when approximately 5% of agricultural land is lost. Therefore, as with the SSP 2 and 3 results the greatest consequence of land loss will be seen in Africa and the Middle East (Fig. 4). Food Secure scenarios offer the

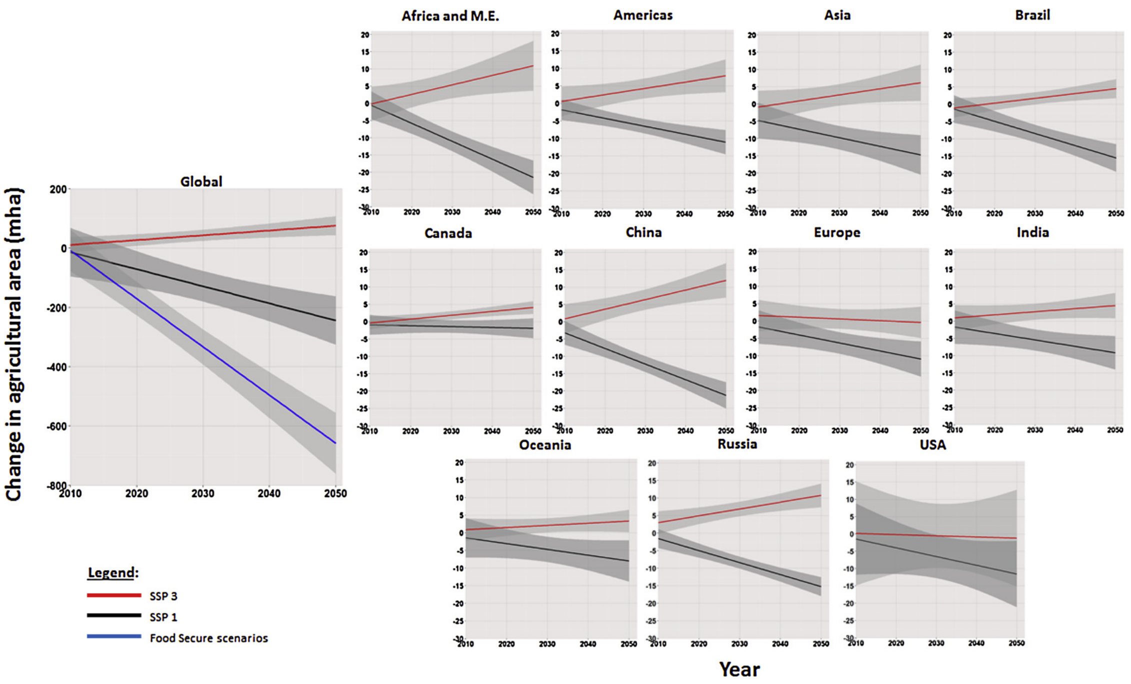

Fig. 3. Change in the total agricultural area (cropland and pasture) between 2010 and 2050 for SSP1 and SSP3, and Food Secure scenarios relative to the SSP2 (baseline) scenario. All values are in millions of hectares (Mha) Straight lines were fitted between 2010 and 2050 using the mean of all land use change models, with grey areas representing the 95% C.I. across models.

greatest chance to mitigate against the impacts of productivity losses as the significant reduction in the amount of land required to feed a growing population (S.I 2 a, b), relative to modelled baselines is such that vulnerable land is not necessary for maintaining food production even at the higher end of our estimates. This suggests that dietary change can insulate food production systems from climate change or climate shocks (Fig. 4a), in a more effective manner than technological gains alone. However, it is important to note that for the purposes of this study only global changes in agricultural land areas were investigated, due to differences in the spatial resolutions between modelled outputs. Therefore, a similar analysis of Food Secure scenarios disaggregated to a country or regional level may find that the change in agricultural area between 2010 and 2050 may not be enough mitigate against losses in agricultural land.

3.4. *Trade patterns and the importance of agriculture to regional economies*

Losses in agricultural land, and the subsequent shortfall in production of different commodities, may have a knock-on effect on both regional economies and current trade flows. In the absence of model-specific outputs on trade flows between 2010 and 2050, statistics on long term regional trade flows and indicators of the economic value of agriculture were extracted from FAOSTAT (2018). For example, domestic supplies of agricultural commodities are often based on a combination of both production and imports to make up demand short falls. Currently, in large regions such as Europe, Africa and the Middle East, and Asia, trade is dominated by regional partners (Fig. 5). However, trade imbalances between regions such Africa and the Middle East and Europe can be skewed by demand for commodities. More specifically African and Middle Eastern countries predominantly import wheat and cattle meat from Europe (Fig. 6) and despite a positive trade balance

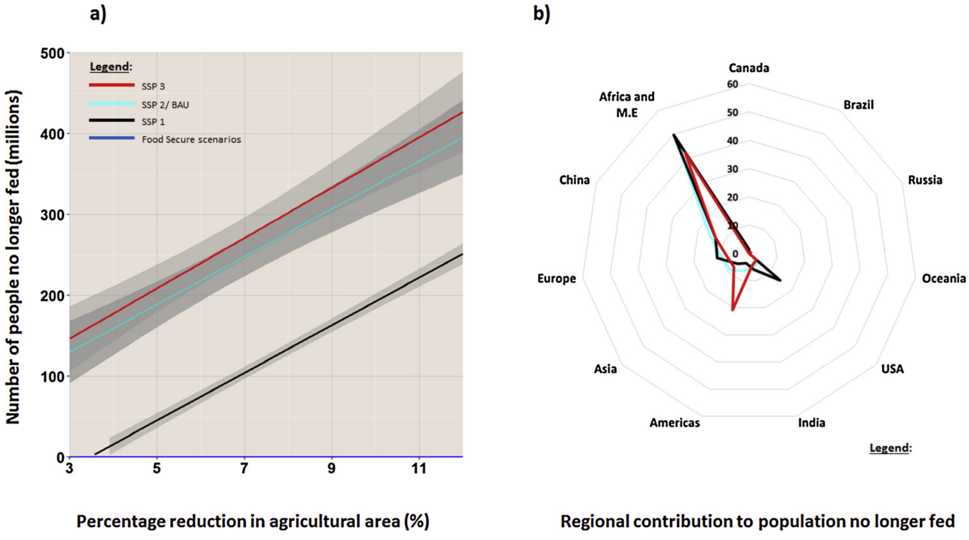

Fig. 4. (a) The global number of people no longer fed for each SSP or Food Secure scenario if the total area of agricultural land (cropland and pasture) is removed from production. Straight lines were fitted based on the mean of all land use change model outputs, with grey areas representing the 95% C.I. across models. Values on the x-axis represent quarterly decrease in agricultural area. Note the Food Secure scenario follows the X axis (i.e. everyone is fed despite reduction in the agricultural area): **(b)** Represents the percentage (%) contribution of each region to the global total of people no longer fed in part (a).

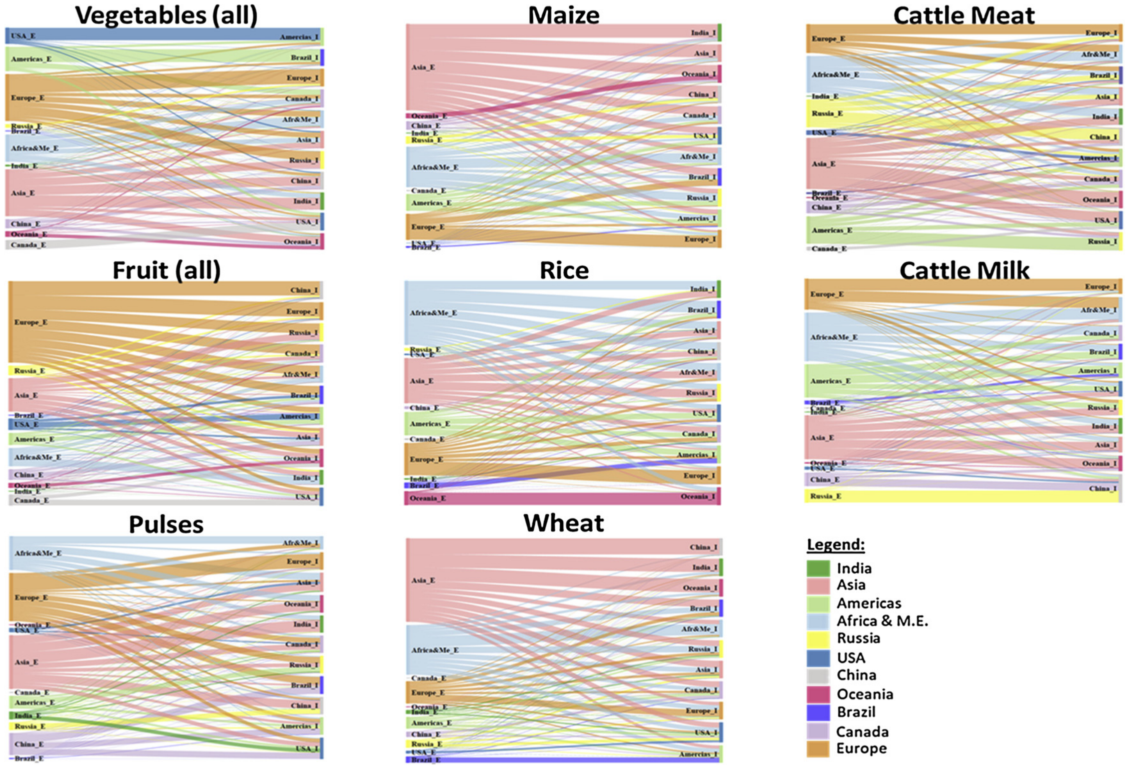

Fig. 5. Trade flow of the different agricultural products between exporting (E) and importing (I) regions. Coloured bands represent the movement of each commodity from exporting to importing region. Band width represents the proportion of total exports of the commodity that reaches each importing regions, Exporting (E) node width represents the number of trading destinations, Importing (I) node width is fixed for all regions.

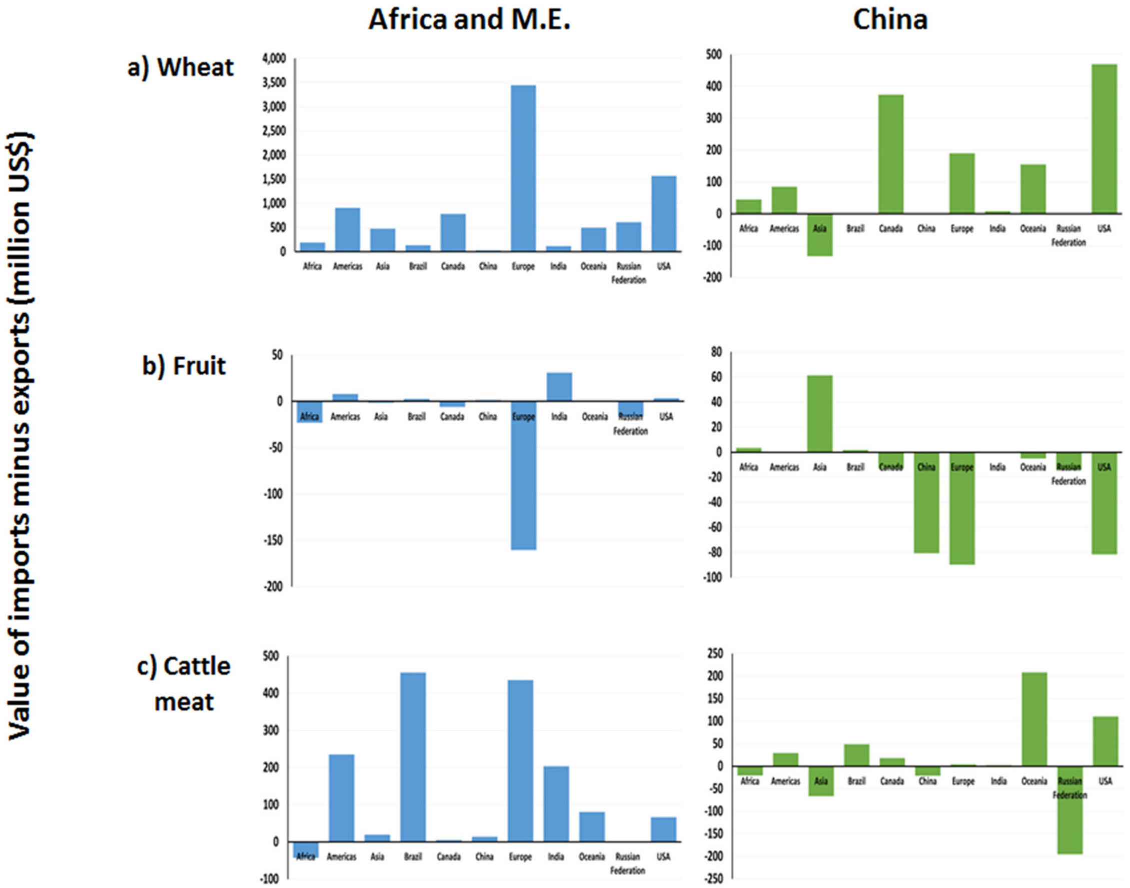

Fig. 6. Trade balances (imports minus exports) of different products traded between Africa and the Middle East and China with other regions, as defined in this study.

Table 2
Statistics on the importance of the agricultural sector in each region.

Region	% of total water withdrawals[a,*]	% increase in population in 2050[a,*]	% of total employment[b,*]	GDP per capita ($) [a,*,§]	Change in gross production value (%)[a,*, §]
Africa + Middle East	67	109	46	4,165	111
Americas	65	41	19	3,704	72
Asia	80	37	39	3,969	31
Brazil	59	21	22	4,119	97
Canada	N/A	26	3	28,203	43
China	80	−7	46	814	138
Europe	26	−3	12	21,218	20
India	92	34	58	447	177
Oceania	49	44	26	11,586	73
Russia[ß]	20	−15	11	3,768	31
USA	41	25	2	32,780	15

[a] FAOSTAT; [b] World Bank; *Values based on long term average, unless otherwise stated; Ɨ Values are based on change from 1970′s to 2000′s.
[ß] Values calculated from 1990′s onwards; § Calculated from values standardised to US$, 2005 prices or millions.

with Europe for fruit (Fig. 6), the value of the total exports is only a fraction of the value of wheat imports. Reductions in trade volumes can propagate into regional food insecurity due to the importance of a given commodity to regional diets, but also the reliance on trade as its source. In Africa and the Middle East, maize and wheat each account for approximately 9% of all food consumed within the region (S.I.3a). However, in 2010, the equivalent of 43% of all maize and 86% of wheat consumed as food originated as an import (S.I.3b), either from within the regional bloc or from other trading partners. If in the future production in all regions is reduced in line with the assessments outlined in section 3.1, but demand increases (Table 2). This can lead to a reduction in the availability of commodities for trade, thereby increasing prices beyond the purchasing power of some countries and consequently contributing to the number of people at risk of no longer being fed. The effects can be further exacerbated by knock effects on local economies as in some regions the value of agriculture in terms of GDP and employment is becoming increasingly (Table 2) critical as a source of income.

It is also important to note that supply chains differ by countries and by commodity (Fig. 6). For instance, China, in which the agricultural share of GDP has increased significantly and is responsible for a large percentage of national employment (Table 2), also imports wheat and meat from cattle. However, China's primary trading partners for these commodities; Canada and Oceania (Fig. 6) are projected as having only ˜1% of land classified as vulnerable (S.1 a-d), so trade flows would not be disrupted, and the trade component of domestic supply may not be vulnerable.

4. Discussion and conclusions

4.1. Model ensemble approach – uncertainties and limitations

The aim of this work was to understand the regional vulnerability of agricultural land to future changes of water availability and water scarcity. By combining outputs from two multi–model ensembles, i.e. multiple GCM outputs coupled to a hydrological model and multi-model land use projections, future trends and uncertainty around land use estimates and changes in water scarcity were assessed both globally and regionally. While the comparison of different model projections could lead to a trade-off in errors between the models (Ehrhardt et al., 2017; Matre et al., 2015) there are several important sources of uncertainty.

As stated previously, differences in model projections of water scarcity and change in baseline run-off estimates tended to be greater between the different GCMs than between the scenarios (SSP and RCP) they were implementing. Both water scarcity and annual runoff were calculated from a single hydrological model, therefore uncertainty in modelled estimates was driven by inputs derived from the different GCMs. As each GCM has its own evolutionary history, structural differences, including inputs used to drive the model and input interactions, differ from model to model. The most discernible manifestation of differences between the GCMs was the modelled changes in precipitation patterns (Carvajal et al., 2017). Some studies have focused on reducing the disparity (Nguyen et al., 2017), by for example correcting biases in modelled precipitation; through selecting 5 model outputs at random, we can use this uncertainty to inform the analysis.

The multiple land use projections in 2050 were also sourced from different model types that ranged from land allocation to general equilibrium models. As with GCMs, differences in the spatial resolution, model processes and component interactions can lead to differences in outputs about the area of agricultural land required to feed a changing population. However, as detailed in Alexander et al (2017), there were significant differences between the initial pasture area (i.e. in 2010) used to drive model simulations. Uncertainty in land cover for different regions, particularly in Africa has been described in other studies (Zoungrana et al., 2015; Valentini et al., 2014), as has the implications land cover uncertainty has on greenhouse gas emission estimates and deforestation rates. In the context of this study, differences between the models in the assumed initial pasture extent means that even under the same scenario, the change in area relative to its baseline differed. This is because land cover classes are used to predict the amount of crop and grass biomass available for use within a defined area. As land allocation or equilibrium models allocate land to match future demand, difference in initial classification means that there are differences in the amount of biomass available for a given activity.

The discrepancies in modelling approaches, that underpin the principal methodology used in this study, as well as the interpretations used here, mean that the results presented here represent a demonstration of trends that may emerge if food production is affected by limited water availability. For example, it is unrealistic to assume that because land is vulnerable, it directly leads to a total loss of all productivity. Moreover, the assessment is reliant on annual estimates of changes in water availability, rather than using estimates based on seasonal changes. As crop, livestock products and other commodities produced on agricultural land tend to be seasonal, this study may overestimate the extent as to which land is vulnerable. Conversely the vulnerability of agricultural areas could be underestimated as not only are uncertainties in modelled precipitation patterns high (Arnell et al., 2011), but because of unexpected results like those found in Oceania. Here zero percent of all agricultural area was found to be vulnerable which is surprising considering Australia is known to have a dry climate. This finding is due to uncertainty in modelled simulations as noted in Arnell et al (2011), here the large spatial scales of the watersheds potentially mask water scarcity but in Australia annual run-off has significant inter-annual variation, so assuming only watersheds with declining water availability may lead to underestimations.

Moreover, an analysis of global extreme weather disasters found that droughts and extreme heat reduced national cereal production by 7% (Lesk et al., 2016). Similarly, recent ensemble modelling analysis investigating the effect of the European heatwave in 2003 found that models tend to underestimate the impact that extreme events have on agricultural production (Schewe et al., 2019).

4.2. Land and regional vulnerability: impacts and challenges

An analysis of trends that emerge from combining the two multi-model ensembles indicate that, given the potential vulnerability of land to increased water scarcity, the land required to feed a growing population envisaged under SSP2 or SSP3 might be unachievable. This is particularly true for Africa and the Middle East, and while this is not an unexpected result, the finding indicates that an additional 6% of the regional population would not be fed under such scenarios. As this study does not consider undernourishment or malnutrition, which already exists in African and Middle Eastern countries today, the effect of the loss of productive land could have significant repercussions, including increasing malnutrition and income reductions / loss of employment.

An examination of the land used to grow some of the most important, in terms of value and consumption, specific commodities also allows for a connection to be made between different components of food production and trade. For example, not all the pasture area in a given region is used for livestock production, so using a dataset that details where grass-fed milk and meat production are located allows the vulnerability of this aspect of food production to be determined. African and Middle Eastern countries have a significant amount of land that supports grass-fed cattle production systems that is classified as vulnerable. Pasture or grassland productivity is strongly linked to mean annual precipitation (Le Houerou et al. 1988; Paruelo et al., 1999; Yang et al., 2008) as well as the inter-annual variability (Sloat et al. 2018) and as some African and Middle Eastern countries have arid climates, energy intake by ruminants in grass fed systems tends to be lower than in, for example, northern European countries (Herrero et al., 2013). Therefore, any reduction in biomass productivity, due to declining water availability, can further reduce animal intake and productivity. Similar analysis was performed for cattle, pig and poultry production systems that are reliant on grain as a food source, but since the results were similar for grass-fed systems, they are not presented here. It is difficult to link the grain food source to animal type, but modelled projections from Röös et al (2017) have shown that current production levels from croplands are insufficient to maintain a protein food supply for livestock in the future. If we assume that croplands produce 50% of the total biomass for animal feed (Herrero et al., 2013), and 12% of global croplands, as identified in this study, are vulnerable to production losses or could be removed altogether, then the shortfall in availability of feed for livestock could only increase.

While trade allows for different countries or regions to maintain adequate food supply, reliance on trade only increases food insecurity rather than creating a more sustainable future. For example, our analysis shows that African and Middle eastern countries import large amounts of wheat, compared to other commodities from Europe, and this trade flow accounts for 45% of global trade in wheat (Enghiad et al., 2017). If then for example wheat production declines in Europe due to water scarcity, a reduction in wheat stocks could increase market prices and impact on food security due to its importance in regional diets.

This is consistent with the findings of Liu et al (2014), when modelling the impact of irrigation shortfalls on crop production and trade. Here commodities produced in regions with the greatest irrigation pressures experienced the greatest increase in price and consequently these commodities were then sourced from international markets. To compensate for shortfalls in wheat, countries within Africa and the Middle east could switch to other major exporters of wheat, such as Canada, which are not expected to be vulnerable to water scarcity. However, competition from other regions with a greater purchasing power could increase demand for Canadian wheat and increase prices accordingly. There is also the assumption in the future Canadian production will increase incrementally to meet demand. Currently agricultural production in Canada threatens supplies of freshwater to its boreal forests, which in turn cover 60% of its land mass (Liu et al., 2015). For Canada to preserve the ecosystem services these forests provide (Liu et al., 2015) and maintain any commitments to climate change accords, large scale land use change from forest to croplands may be stymied.

Liu et al (2014) indicated that to maintain productivity for domestic and trade supplies, approximately 7.6 million hectares of land would need to be converted to in cropland. Therefore, to avoid large scale LUC, intensification particularly in regions such as Africa and M.E. could theoretically double current crop productivity (World Bank, 2012). To achieve this, investments in irrigation could be necessary to extend the growing season (Grafton et al., 2015; Meng et al., 2017). However, increased demand for water means that increasing the amount of irrigated land must be coupled to crop yield improvement (Liu et al., 2017; Grafton et al., 2017), improvements in crop water use efficiencies and nutrient management to reduce the environmental impacts associated with agriculture (Elliott et al., 2014; Mueller et al., 2012b). Such strategies are often incorporated into model implementation of SSP1 types futures, and results indicate that the slight reduction in agricultural land area, could, in theory, protect against some of the impacts of losses in agricultural land identified in this study.

Multiple studies have shown that shifts to sustainable diets, and efforts to tackle food waste, offer the greatest potential to create an agricultural production system that is sustainable. This is because there is (i) a reduction in GHG emissions from land use associated with the production of animal - based commodities (Gonzalez et al., 2011; Abbade, 2015; Westhoek et al., 2014; Sabaté et al., 2015) (ii) increase agricultural efficiencies as for example in the USA one fifth of the current land, fertilisers and water is used in the production of food that is not consumed (NRDC, 2017) and (iii) a reduction in water consumption (Jalava et al., 2016). The analysis here demonstrates that, globally, the significant reduction in agricultural area required to feed an increasing population, as demonstrated under sustainable and food secure scenarios, mean that risks to production due to water scarcity are reduced, thereby mitigating against the risks of food insecurity particularly in regions such Africa and the Middle East.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.gloenvcha.2019.101944.

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