The impact of UK food and bioenergy imports on global land use under future socioeconomic scenarios (UK-SSPs)

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1 Abstract

Food imports are a critical part of the UK's food supply, accounting for nearly half of all food consumed domestically. Reliance on imports raises concerns about food security as well as environmental impacts due to land use associated with imported commodities (the land footprint). Previous studies estimate that approximately 10 Mha of agricultural land is used globally outside the UK to produce food destined for the UK. However, previous methods fail to account for marginal yield effects as well as present and future feedbacks between food prices, demand, production, and international trade. Using a global land use modelling framework, LandSyMM, we produce estimates of the global land use impact of UK food and bioenergy imports. We simulate food demand, agricultural production, and trade under a range of global and UK-specific socioeconomic and climate scenarios. We estimate that 42 Mha of agricultural land could be currently linked to UK food and bioenergy imports, trending towards 22-46 Mha by 2070-2079. Given 17 Mha of agricultural land in the UK, our results suggest that UK food imports could have a disproportionate impact on global land use compared to domestic production and should be an important focus for evaluating the environmental consequences of food production.

2 Introduction

The United Kingdom is a net importer of food with imports accounting for 46% of total food consumption (Defra, 2021). Globally, this puts the UK third among the largest net importing countries (in terms of net trade value), behind China and Japan (FAO, 2022). The UK's reliance on food imports leaves the country's food system vulnerable to global shocks including climate change, international conflict, and market shocks (Macdiarmid *et al.*, 2018; Defra, 2021). Recent global events including the COVID-19 pandemic and the war in Ukraine have exemplified the importance of understanding the resilience of the global food system and international trade to shocks (Moran *et al.*, 2020; Alexander *et al.*, 2023).

There are also concerns about the growing impact of UK food imports on associated land use, land use change (LULCC) and greenhouse gas emission abroad (de Ruiter *et al.*, 2016). This issue is not unique to the UK, with numerous studies linking international food trade to negative environmental impacts. For example, the EU's increasing demand for biodiesel and animal feed is a major driver of deforestation in tropical countries (Fuchs, Brown and Rounsevell, 2020). Globally, international trade is responsible for 29-39% of deforestation-related GHG emissions (Pendrill *et al.*, 2019). However, there are considerable differences in the environmental impact of different food groups (Poore and Nemecek, 2018), and some imported crops can have a lower environmental impact than the equivalent produced domestically (Webb *et al.*, 2013). This illustrates the complexity of linkages between food imports and LULCC which are dependent on multiple interactions between producers, importers, and consumers.

The land area associated with agricultural imports and exports has been termed the land footprint, embodied land or virtual land, among others. Between 1986 and 2016, the land footprint associated with global agricultural trade increased from 128 Mha to 350 Mha, representing nearly a third of global arable land use (Chen and Han, 2015; Qiang *et al.*, 2020). This highlights the significance of international trade for global land use patterns.

Previous studies generally use one of two approaches to estimate land footprints – biophysical accounting and Multi-Region Input Output (MRIO) analysis. Biophysical accounting relies on reported yields and detailed trade tables to calculate the area of land in each country or region associated with trade flows (Bruckner *et al.*, 2015). In contrast, MRIO models link national input-output tables of financial transactions between a country's economic sectors with tables of international trade flows (Wiedmann *et al.*, 2011; Bruckner *et al.*, 2015). In an environmentally-extended MRIO, production factors are added to the MRIO framework, allowing for the estimation of the environmental impact of each unit of final demand (Wiedmann *et al.*, 2011). An advantage of the MRIO framework is that it can incorporate indirect biomass flows which are generally not included in biophysical accounting approaches (Kastner *et al.*, 2014).

While differences in estimates of land use footprints are to be expected from different methodologies, some case studies produce contradictory results. For example, a comparative analysis by Kastner et al. (2014) shows that estimates of net cropland area embodied in China's trade range from -17 Mha to 19 Mha (i.e. from a net export to a net import of land). Biophysical accounting and MRIO analyses also ignore marginal yield effects and the spatial explicitness of land footprints by averaging yields at national or higher levels (Godar *et al.*, 2015). Each additional unit of production may require increasing amounts of inputs (land, fertiliser, irrigation etc.) and therefore the land use impact of exported commodities may be considerably different than that of domestic consumption.

Interactions between trade flows, domestic production, commodity markets, and consumer demand add further layers of complexity which cannot easily be captured by simpler accounting-based land footprint models. Land footprints have been linked to factors such as affluence, with high income countries displacing a larger proportion of their land use abroad (Weinzettel *et al.*, 2013; Qiang *et al.*, 2020). Changes in income distribution, dietary shifts and population growth are key factors which determine the patterns of food trade globally (Qiang *et al.*, 2020). Considering these interactions is particularly important when attempting to project land footprints into the future.

The marginal impact of UK imports on global land use, and how it varies under a range of future socioeconomic and climate scenarios, has not previously been assessed. We explore these impacts using a spatially detailed global land use modelling framework by comparing baseline scenarios with counterfactual scenarios which remove the UK from international markets. This work distinguishes the "land footprint" - the physical area of land used to produce traded goods - and the "land use impact" which represents a combination of the land footprint and indirect effects on global land use caused by UK's trade patterns.

3 Methodology

3.1 Model architecture

3.1.1 LandSyMM

The Land System Modular Model (LandSyMM; https://landsymm.earth) is a spatially explicit model of the global land system which couples a number of sub-component models of land use decision making, vegetation growth, food demand, and international trade. Here, we coupled three components of LandSyMM to investigate the UK's global land use impact and are described as follows.

3.1.2 LPJ-GUESS

The Lund-Potsdam-Jena General Use Ecosystem Simulator (LPJ-GUESS) is a dynamic global vegetation model which simulates plant and ecosystem processes including vegetation and soil carbon dynamics, the nitrogen cycle, plant physiological responses to climate and human activity, and disturbance (Smith, Prentice and Sykes, 2001; Smith *et al.*, 2014). LPJ-GUESS has been shown to produce estimates of global gross primary productivity consistent with other sources (Ito *et al.*, 2017) and can simulate realistic crop yield responses to changes in CO2 levels and nitrogen management (Olin *et al.*, 2015). Here, LPJ-GUESS is used to generate potential yields for seven food crops, pasture, and a second-generation bioenergy crop (*Miscanthus*) under a range of climate scenarios.

3.1.3 PLUM

The Parsimonious Land Use Model (PLUM) simulates land use and land use change from changes in demand for food commodities and bioenergy, changes in crop yields, and international trade (Engström *et al.*, 2016; Alexander *et al.*, 2018). Food demand is projected using the MAIDADS demand system (Gouel and Guimbard, 2019) which uses per capita income (from SSPs) and commodity prices (modelled endogenously in PLUM) to calculate demand for seven food groups. Regional demand for second generation bioenergy is taken from the IIASA SSP Database and disaggregated to country level based on potential *Miscanthus* yields.

During each time step, PLUM uses least-cost optimisation to determine land use factors including crop and pasture area, fertilizer input, irrigation, and other intensity factors. Crop and pasture yields are interpolated for a continuous range of fertilizer input and irrigation using yield tables generated by factorial experiments in LPJ-GUESS. Irrigation is constrained on water basin level by the estimated surface water runoff modelled in LPJ-GUESS. The model is constrained to produce sufficient food and bioenergy to meet demand, either through domestic production or through imports. A single international market allows countries in PLUM to import and export commodities. Commodity prices are adjusted based on the net balance of imports and exports.

3.1.4 CRAFTY

CRAFTY (Competition for Resources between Agent Functional TYpes) is an agent-based land use modelling framework which simulates decision making across a range of land uses, over large geographical extents (Murray-Rust *et al.*, 2014). In CRAFTY, land managers are represented by agent functional types (AFT) which utilise capitals (land productivity, labour, knowledge, among others) to supply a range of ecosystem services (ES) such as food, timber, and recreation. The value of the ES generated by each AFT is determined by the balance of demand and supply for the ES. Demand for ES is exogenous and not modelled in CRAFTY.

In this study, we use CRAFTY-GB – a UK implementation of the CRAFTY model. CRAFTY-GB has been previously used to evaluate the land use consequences of UK-SSPs at a 1km^2 resolution, showing large scenario-dependent differences in land use intensity and provision of ecosystem services (Brown *et al.*, 2022). In contrast to other land use models, CRAFTY allows for dynamic, non-optimising simulation of land use decision making by a variety of AFTs. In combination with detailed UK-SSPs storylines, this produces distinct future scenarios of land use in the UK which we use here to explore the global impact of UK's food and bioenergy trade.

3.2 Scenario construction and simulation

3.2.1 Description of SSPs and UK-SSPs

We chose six SSP-RCP (Shared Socioeconomic Pathways; Representative Concentration Pathways) combinations to represent a range of plausible future socio-economic trajectories, both in the UK (UK-SSPs) and globally. This includes one scenario for each of the five SSPs with corresponding RCPs (SSP1-RCP2.6, SSP2-RCP4.5, SSP3-RCP6.0, SSP4-RCP4.5, SSP5-RCP8.5), and an additional SSP2 scenario with a high RCP (SSP2-RCP8.5). The following scenario descriptions are summarised from O'Neill et al. (2017) for global SSPs, and Pedde et al. (2021) for UK-SSPs.

Globally, SSP1-RCP2.6 represents a shift towards sustainability characterised by a focus on environmental protection and investment in education, health, and international cooperation. Lower population growth and reduced consumption mean less pressure on the environment. In the corresponding UK-SSP1 scenario, worsening societal issues relating to environmental degradation initiate a technological and policy "green-race" which leads to high levels of sustainability in the UK by the end of the century.

SSP2-RCP4.5 and SSP2-RCP8.5 are business-as-usual scenarios and can be seen as extrapolations of current socio-economic and demographic trends with moderate population and economic growth. The latter scenario with RCP8.5 is an alternative parameterisation with high levels of radiative forcing which we use here to explore some of the uncertainty associated with projections of future GHG emissions.

SSP3-RCP6.0 is marked by lack of international cooperation, regional conflict and weak global institutions leading to a lack of concerted effort in addressing environmental and societal problems. Population growth is uneven, with higher growth in developing countries. Resource use and fossil fuel intensity are high with little progress towards sustainability. The UK-SSP3 scenario is particularly severe, with high likelihood of institutional collapse and a return to subsistence lifestyles.

SSP4-RCP4.5 is characterised by high levels of international inequality where the gap between higher and lower income communities progressively widens. Environmental action is mostly focused internally with low levels of international cooperation. In UK-SSP4, deregulation of the business sector and erosion of public welfare leads to extreme levels of inequality, with a majority living in poverty.

In SSP5-RCP8.5, fossil-fuel-driven development results in relative prosperity and rapid development globally. The focus on economic growth means that global environmental issues are neglected and GHG emissions are high. For the most part, the UK remain relatively prosperous in UK-SSP5 until severe environmental degradation begins to threaten societal stability towards the end of the century.

3.2.2 Food and bioenergy demand

CRAFTY relies on extraneous data to specify food and bioenergy demand. We used PLUM to simulate country-level demand for agricultural commodities for each of the six scenarios. Runs were initialised in 2010 and proceeded on an annual timestep until 2080. Projected UK food demand from PLUM was mapped to FAO food categories which were then mapped to CRAFTY demand categories.

Using demand outputs from PLUM, we used CRAFTY to simulate land use in the UK for each scenario. Production levels from CRAFTY were then mapped back to PLUM categories. Unlike PLUM, CRAFTY does not constrain production to meet demand but instead allows production to emerge from agent competition for land. Consequently, production levels mapped from CRAFTY to PLUM can differ from the original demand levels generated in PLUM. Any shortfall or surplus in food production was added to import or export levels respectively. UK commodity demands were rebased to match observed data in 2010. Final UK food and energy crop import balances are shown in figure 1.

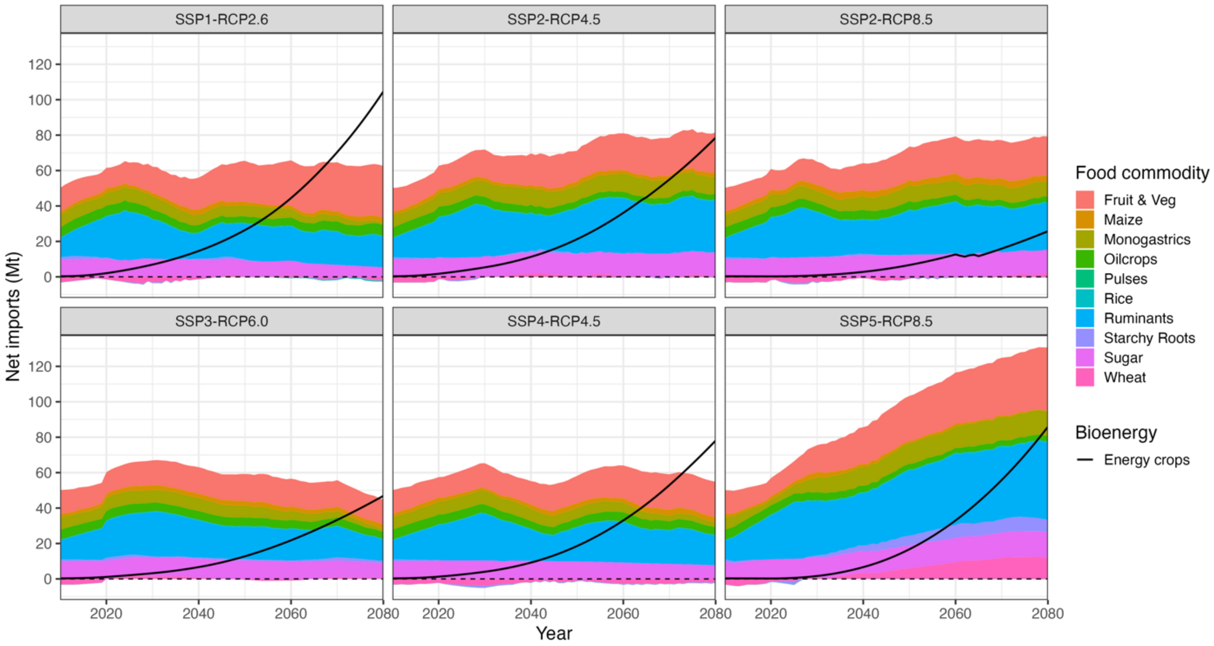


Figure 1 – Modelled UK net import levels of food commodities and energy crops, by scenario (panels). Positive values represent net imports and negative values represent net exports.

3.2.3 Scenario simulation

For each scenario, we used PLUM to produce a pair of runs: a baseline run and a counterfactual run. In the baseline run, the usual UK country agent in PLUM was replaced with outputs generated by CRAFTY in a one-way CRAFTY to PLUM coupling. Demand and land use in other countries were simulated by PLUM. In the counterfactual run, the UK was omitted from the simulation. Since countries in PLUM interact only through a single global international market, removing the UK's influence on global trade balances removes the UK's impact on global land use.

PLUM is initialised with observed food production and consumption data from the FAO, and land cover distributions from LUH2 (Hurtt *et al.*, 2020), among other datasets. As the model is not constrained to reproduce initial starting conditions, a calibration or 'spin-up' sequence is first done before running future scenarios. Counterfactual scenarios were initialised from a calibration run where the UK has been removed from the simulation. The resulting state is a hypothetical world without the UK's influence on global land use. However, given that the model is initialised on historical data (which includes the UK), some of the UK's influence may remain after the calibration run.

To simulate uncertainty in our projections, we used Monte-Carlo methods to sample a range of model parameters consistent with each SSP scenario. Parameter distributions were informed by SSP storylines and the authors' expert opinion. Thirty Monte-Carlo repeats were used for each scenario.

Although the focus of this study is primarily on the UK's food and bioenergy imports, we also allowed the net export of commodities from the UK. The results of this study should technically be interpreted as the net effect of UK food trade. However, across all scenarios, exports comprised a minor proportion of total UK trade (on average <2% of total trade volume) and should therefore have negligible impact on results.

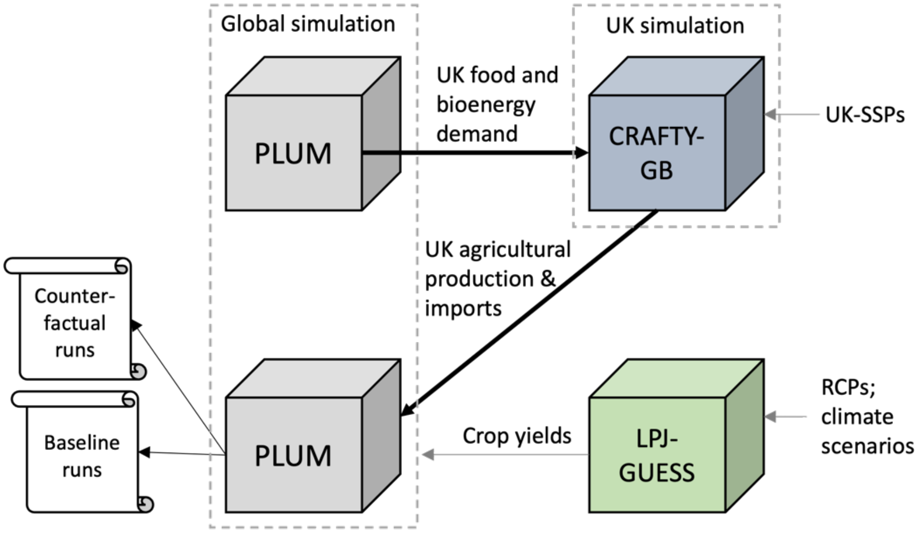


Figure 2 – Schematic diagram of the modelling framework, showing the main couplings between the different component models used here.

4 Results

4.1 Future trends in the UK's global land use impact

Across all scenarios and all time periods considered here, global agricultural area (excluding the UK) is greater in baseline scenarios compared to counterfactual scenarios which exclude the UK (figure 3). We estimate that in the period 2010-2019, 19.0 Mha (IQR: 15.3, 21.7) of cropland and 23.7 Mha (IQR: 19.6, 25.9) of pasture could be linked to the impact of UK food and bioenergy imports on global land use. This was further associated with 36.0 km^3 (IQR: 5.2, 68.6) of additional irrigation and -1.2 Mt (IQR: -2.6, 0.2) nitrogen fertilizer used compared to counterfactual scenarios. Altogether, we estimate that food and bioenergy commodities imported into the UK may currently be linked to 41.9 Mha (IQR: 37.8, 44.9) of additional agricultural land globally.

It is important to note that these figures do not represent the physical land area and inputs used to produce food imported to the UK. Instead, they represent the marginal impact that UK food imports have on global land use and the impact of indirect effects caused by interactions between global trade balances, commodity prices, and food demand.

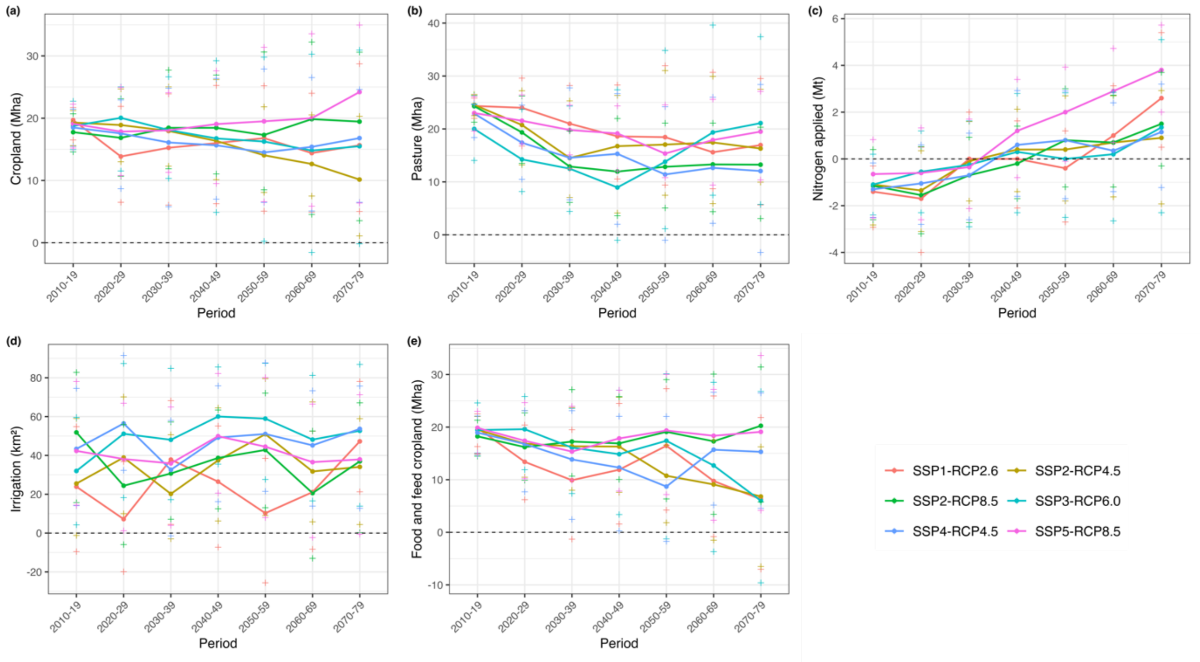


Figure 3 – The global impact of UK food and bioenergy imports on global (a) cropland area, (b) pasture area, (c) nitrogen fertilizer use, (d) irrigation water withdrawn, and (e) food and feed crop area. Median values are shown by solid lines and interquartile ranges are indicated by crosses. Positive values indicate greater global land use due to UK's food and bioenergy trade compared to a counterfactual scenario which excludes the UK from international markets.

The scenarios show some initial divergence in the UK's global land use impact and these differences generally amplify over time, albeit with large variation. Under SSP5-RCP8.5, the UK's global cropland area impact increases to 24.2 Mha (IQR: 6.4, 35.0) in the period 2070-2079 (figure 3a). In contrast, under SSP2-RCP4.5, the cropland area impact decreases to 10.2 Mha (IQR: 1.1, 20.3). Scenarios SSP1-RCP2.6, SSP2-RCP8.5, SSP3-RCP6.0, and SSP4-RCP4.5 show a weaker trend with 15.7 Mha (IQR: 5.0, 28.7), 19.5 Mha (IQR: 3.6, 30.6), 15.5 Mha (IQR: -0.18, 30.9), and 16.9 Mha (IQR: 6.4, 35.0) of cropland in 2070-2079, respectively.

If we exclude cropland used for energy crops (i.e. only including food and feed crops), the UK's cropland area impact remains stable or decreases in all scenarios (figure 3e). For SSP5-RCP8.5, in contrast to total cropland area impact, the food and feed cropland area impact is considerably lower in 2070-79 at 19.1 Mha (IQR: 4.2, 33.6). The largest decrease is seen under SSP3-RCP6.0 with the food and feed cropland area impact falling to 6.00 Mha (IQR: -9.6, 26.8) in 2070-2079.

The UK's impact on global pasture area shows a negative trend across most scenarios, falling to 12.1 Mha (IQR: -3.3, 28.4) under SSP4-RCP4.5, and 13.3 Mha (IQR: 3.1, 20.3) under SSP2-RCP8.5 in 2070-2079 (figure 3b). SSP1-RCP2.6 and SSP2-RCP4.5 show more moderate decreases to 17.0 Mha (IQR: 5.7, 29.6) and 16.3 Mha (IQR: 10.0, 27.5), respectively. The smallest change in pasture area impact is seen in SSP3-RCP6.0 and SSP5-RCP8.5, with 21.1 Mha (IQR: 5.8, 37.4) and 19.5 Mha (IQR: 10.4, 27.1), respectively. However, the trend under SSP3-RCP6.0 is more variable over time with decreasing pasture area impact until 2040-49 (falling to 9.0 Mha [IQR: -1.0, 27.4]) and then rising rapidly.

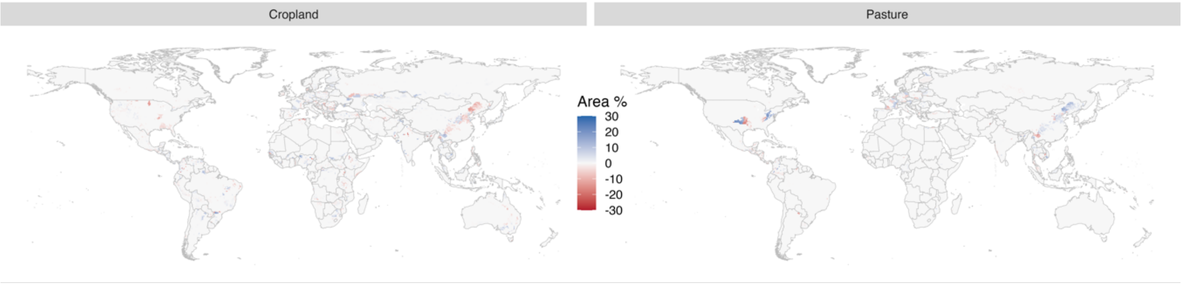
We project a strong trend in the UK's global nitrogen fertilizer use impact which increases to 3.8 Mt (IQR: 2.0, 5.7) under SSP5-RCP8.5 and to 2.6 Mt (IQR: 0.5, 5.4) under SSP1-RCP2.6 by 2070-79 (figure 3c). Under all scenarios, nitrogen fertilizer use impact begins negative (i.e. less nitrogen is applied globally in scenarios with the UK compared to counterfactuals without the UK) and progressively increases, becoming positive by 2070-2079. The smallest increase is seen under SSP2-RCP45 where nitrogen fertilizer use impact reaches 0.9 Mt (IQR: -1.9, 2.9) by 2070-2079. SSP2-RCP8.5, SSP3-RCP6.0, and SSP4-RCP4.5 show comparable increases to 1.5 Mt (IQR: -0.3, 3.7), 1.35 Mt (IQR: -2.3, 5.1), and 1.15 Mt (IQR: -1.2, 3.2).

Finally, the UK's global irrigation impact shows a slight positive trend albeit with large year to year variation and considerable spread between scenarios (figure 3d). By 2070-79, the irrigation impact is highest under SSP4-RCP4.5 (53.7 km^3, IQR: 12.8, 75.7), SSP3-RCP6.0 (52.7 km^3, IQR: 13.9, 86.9), and SSP1-RCP2.6 (47.3 km^3, IQR: 21.3, 78.1). The lowest irrigation impact is seen under SSP2-RCP4.5 (34.1 km^3, IQR: 4.4, 59.0), SSP2-RCP8.5 (37.0 km^3, IQR: 0.2, 67.1), and SSP5-RCP8.5 (38.0 km^3, IQR: -0.63, 71.3).

4.2 Spatial distribution of land use impacts

Although in aggregate the UK is responsible for a net increase in total global agricultural area, interactions between trade levels, commodity prices, and land use optimisation in LandSyMM lead to spatial shifts in agricultural production. Therefore, the impact of UK imports may lead to less agricultural area in some locations, for example if higher commodity prices due to UK demand reduce domestic demand for a given commodity.

(a) SSP2-RCP4.5: 2020



(b) SSP2-RCP4.5: 2080

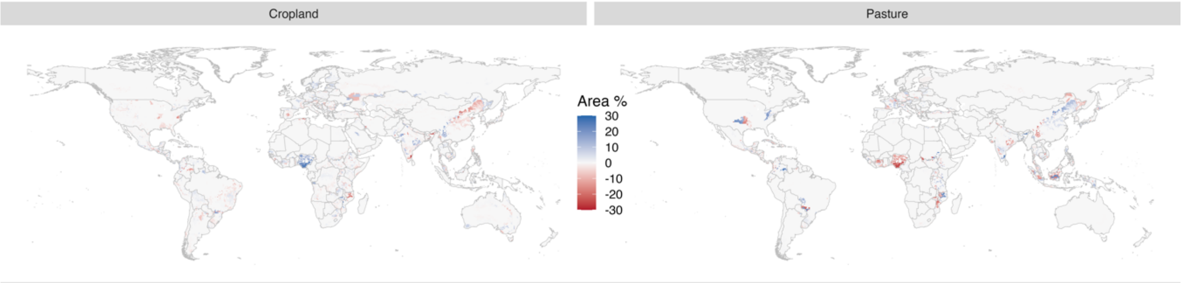
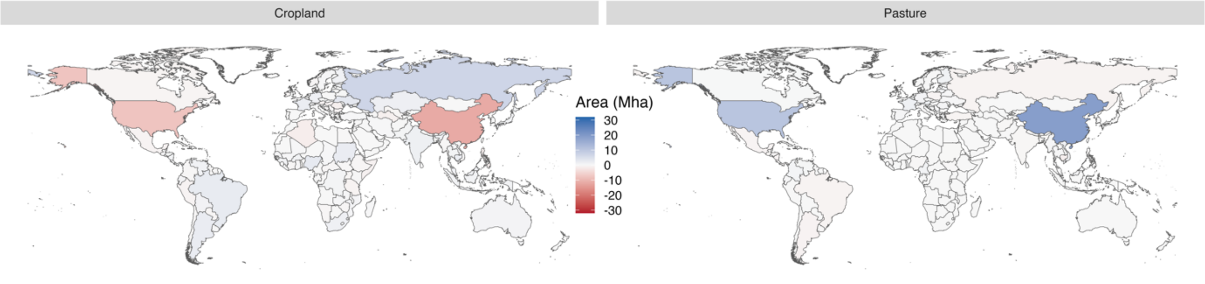


Figure 4 – Spatial distribution of differences in cropland and pasture area associated with UK food and bioenergy imports in (a) 2020 and (b) 2080, under SSP2-RCP4.5. Differences in area are expressed as a percentage of the total land area in each grid cell.

Figure 4 shows the spatial distribution of differences in cropland and pasture cover associated with UK food and bioenergy imports for a single representative run under SSP2-RCP4.5. Given that UK food imports account for less than 3% of total global food imports (FAO, 2023), any impact of UK food imports on global land use is expected to be small. In 2020 (figure 4a), the average difference in land cover across all grid cells which can be attributed to UK imports is 0.038% for cropland and 0.073% for pasture. However, some grid cells show as much as 30% difference suggesting that even a small change in global trade balances can have large effects on the distribution of land use globally.

To better visualise the net effect of differences in land cover areas, we aggregated results to country level (figure 5). We find the impact of UK food and bioenergy imports on agricultural land cover differs considerably between countries. The largest differences in cropland area between the baseline and counterfactual scenarios are seen in major exporting countries including Russia (7.0 Mha), USA (-7.9 Mha), and China (-11.9 Mha) (figure 5a). China and USA also show the largest net difference in pasture area (18.8 Mha and 10.5 Mha, respectively). These patterns largely persist in the future, with some regional variation (figure 5b).

(a) SSP2-RCP4.5: 2020



(b) SSP2-RCP4.5: 2080

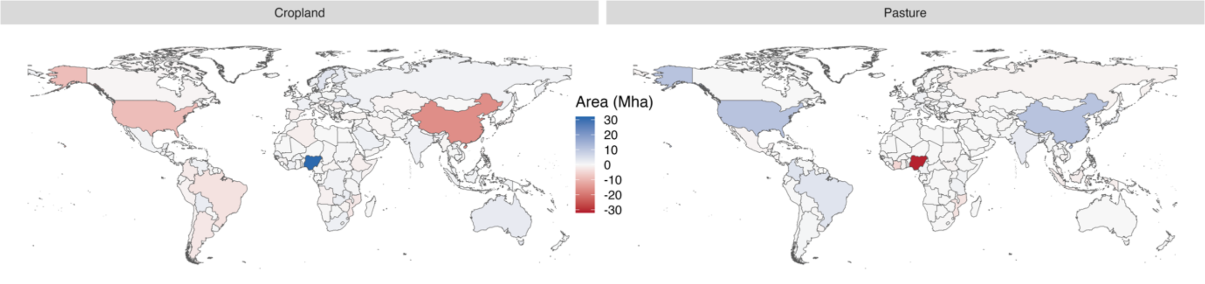


Figure 5 – Differences in cropland and pasture cover associated with UK food and bioenergy imports in a) 2020 and b) 2080 under SSP2-RCP4.5, aggerated to country level.

We also observe that, within each country, increased cropland area is generally associated with decreased pasture area and vice versa. Changes in global trade balances and therefore commodity prices are likely impacting competition between different land uses (pasture and cropland) which leads to spatial shifts in agricultural production. Displacement between cropland and pasture can also be observed locally on a smaller scale (figure 4), suggesting that these shifts can occur on multiple spatial levels.

4.3 Calculating the UK's land footprint using biophysical accounting

Our methodology differs from previous studies on land footprints by explicitly modelling the indirect impacts of food imports on global land use through changes in commodity prices and demand. As such, we are not attempting to replicate previous results but rather illustrate an alternative approach to assessing the global impact of trade. However, given that out results include spatially explicit simulation of crop yields, country level demand and trade flows, we can also calculate the UK's land footprint using biophysical accounting. This gives us a point of comparison against previous studies.

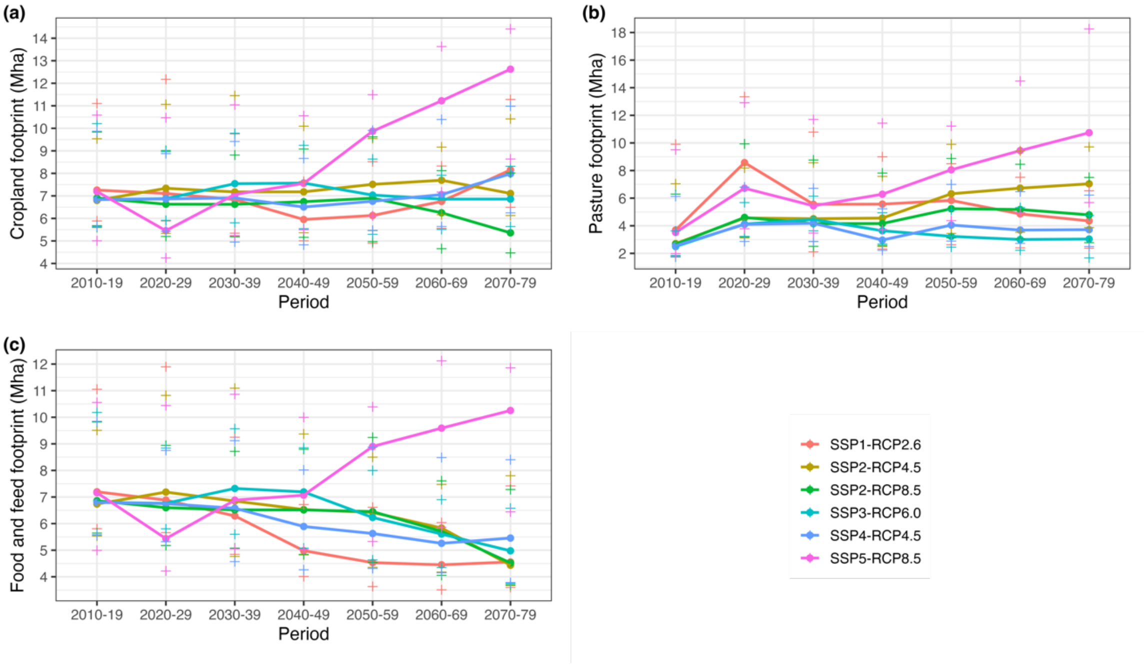


Figure 6 – Land footprint of UK food and bioenergy imports as calculated using the biophysical accounting method for a) cropland, b) pasture, and c) food and feed cropland.

We estimate that for the period 2010-2019, the UK's global land footprint was 7.0 Mha (IQR: 6.4, 7.9) of cropland and 2.8 Mha (IQR: 2.3, 3.8 Mha) of pasture. For most scenarios, the cropland footprint shows little trend over the next century except for SSP5-RCP8.5 where it is expected to increase to 12.6 Mha (IQR: 11.5, 13.3) (figure 6a). In contrast, the UK's pasture footprint increases in all scenarios by 2070-79 albeit with considerable variation between the scenarios (figure 6b). The largest increases are seen in SSP5-RCP8.5 and SSP2-RCP4.5 – 10.7 Mha (IQR: 8.9, 12.6) and 7.0 Mha (IQR: 4.8, 8.2) in 2070-79, respectively.

Excluding bioenergy crops, we find that the UK's cropland footprint generally shows a decline over time for most scenarios (figure 6c). As before, the exception is SSP5-RCP8.5 where cropland footprint increases considerably to 10.3 Mha (IQR: 9.4, 10.8). In contrast, under SSP2-RCP4.5 cropland footprint declines to 4.4 Mha (IQR: 4.1, 5.7), less than half that of SSP5-RCP8.5.

5 Discussion

To our knowledge, our study is the first to evaluate the UK's global land use impact under a range of future socioeconomic scenarios (SSPs). Despite a large degree of uncertainty, our novel estimates of the global land use impact of UK food and bioenergy imports are considerably higher than estimates of the UK's land footprint using accounting-based methods. Unlike previous studies, our work explicitly attempts to estimate the UK's marginal land use impact while allowing for feedbacks between food demand, production, and trade. We believe this represents a more complete picture of how changes in production or consumption impact the rest of the world.

A study by de Ruiter et al. (2017) estimates the UK's global land footprint due to food imports to be approximately 10.2 Mha in 2010, composed roughly in equal parts cropland and pasture. Using our results and similar methodology, we obtain an identical estimate of 10.2 Mha (IQR: 9.2, 11.7) for the period 2010-19. This contrasts with our estimate of the UK's global land use impact which is four times higher (42 Mha). Compared to the land footprint, the total land use impact includes the indirect effects of UK imports on global commodity prices which in turn affect commodity demand, dietary preferences, and land use decisions. These interactions can amplify the impact of international food trade and lead to changes in the spatial patterns of land use.

Our results suggest that the UK's total global land use impact will remain stable or decline over the next 60 years. On average, across all scenarios, the total global agricultural area impact is projected to be 33.0 Mha (IQR: 21.9, 44.5) in the period 2070-79. This corresponds to a decline of 21% from current levels. Both cropland and pasture area impacts are expected to decline, although the latter shows a more consistent trend across scenarios. Furthermore, across all scenarios we observe an increase in global nitrogen fertilizer use attributable to UK imports. This highlights a contrasting trend to certain scenarios, particularly SSP1, in which total global fertilizer use is modelled to decrease and suggests that the UK's food and bioenergy import patterns may lead to marginally greater intensification of agriculture globally.

The impact of UK imports on global land use varies considerably between countries (figure 5). Countries react differently to changes in global trade balances due to a combination of factors including differences in dietary preferences, agricultural subsidies, trade barriers, and yield potentials. In LandSyMM, interaction between countries is mediated by a single international commodity market with no explicit bilateral trading. While bilateral trade agreements could lead to different patterns of land use, projecting these into the future is difficult and highly uncertain. Our framework allows us to make future projections of international trade without making explicit predictions of trade policies.

Much of the focus within UK agricultural policy has been on reducing the environmental impacts of domestic food production, while less attention has been paid to food imports. Despite imports accounting for around half of food consumption, 64% of cropland-related GHG emissions associated with UK food supply are located abroad (de Ruiter *et al.*, 2016). Our results suggest that although trade which prioritises sustainable production may have lower direct impacts, it could still potentially lead to large indirect impacts due to interactions between international markets and global land use. The environmental impact of UK imports depends on the characteristics of exporting countries including environmental standards, biodiversity, and agricultural productivity which are not explored here. Reducing the UK's reliance on imports also comes with trade-offs due to competition for land between food production, timber production and nature conservation.

Although international agricultural commodity trade has been linked to numerous environmental impacts (Lenzen *et al.*, 2012; Pendrill *et al.*, 2019; Fuchs, Brown and Rounsevell, 2020), it nevertheless remains an important factor in global food security. Less than a third of the world's population can meet their demand for major crops from local production within 100 km, highlighting the importance of food trade for food accessibility (Kinnunen *et al.*, 2020). While reliance on imports can leave countries exposed to global supply shocks, in the long term, greater integration across international markets can also mitigate food security risks such as price volatility caused by climatic extremes (Baldos and Hertel, 2015; Chen and Villoria, 2019).

6 Conclusion

The impact of food consumed in the UK reaches far beyond the UK's borders. Our results suggest that previous estimates of the UK's land footprint could be underestimating the total land use impact of UK agricultural imports by not considering interactions between global trade balances, commodity prices and demand. The UK's Net Zero Strategy makes special provisions to support low carbon farming practices, increase tree planting and restore carbon-rich habitats such as peatland (BEIS, 2021). However, there is insufficient analysis of how these land-based mitigation measures could impact the UK’s overall food supply balance. Large shifts in UK land use patterns could potentially lead to displacement of agricultural production to other countries and lead to negative environmental consequences which could partly negate the UK’s efforts to decarbonise the food system. It is therefore critical that we explore the global impact of domestic land use policies. Further work could use our results to examine the global environmental impact of UK imports on key factors such as GHG emissions and biodiversity.

7 References

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8 Supplementary figures

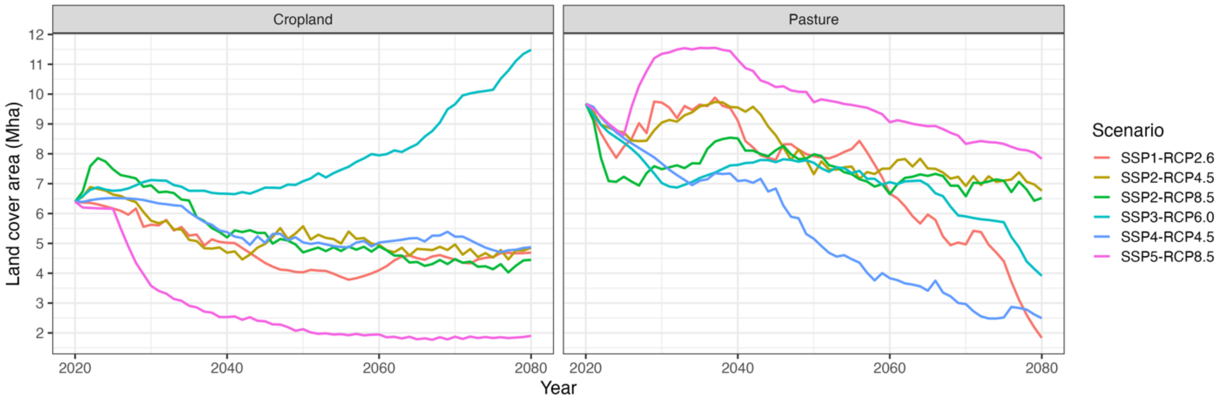

Figure S1 – Simulated UK cropland and pasture area in CRAFTY-GB.

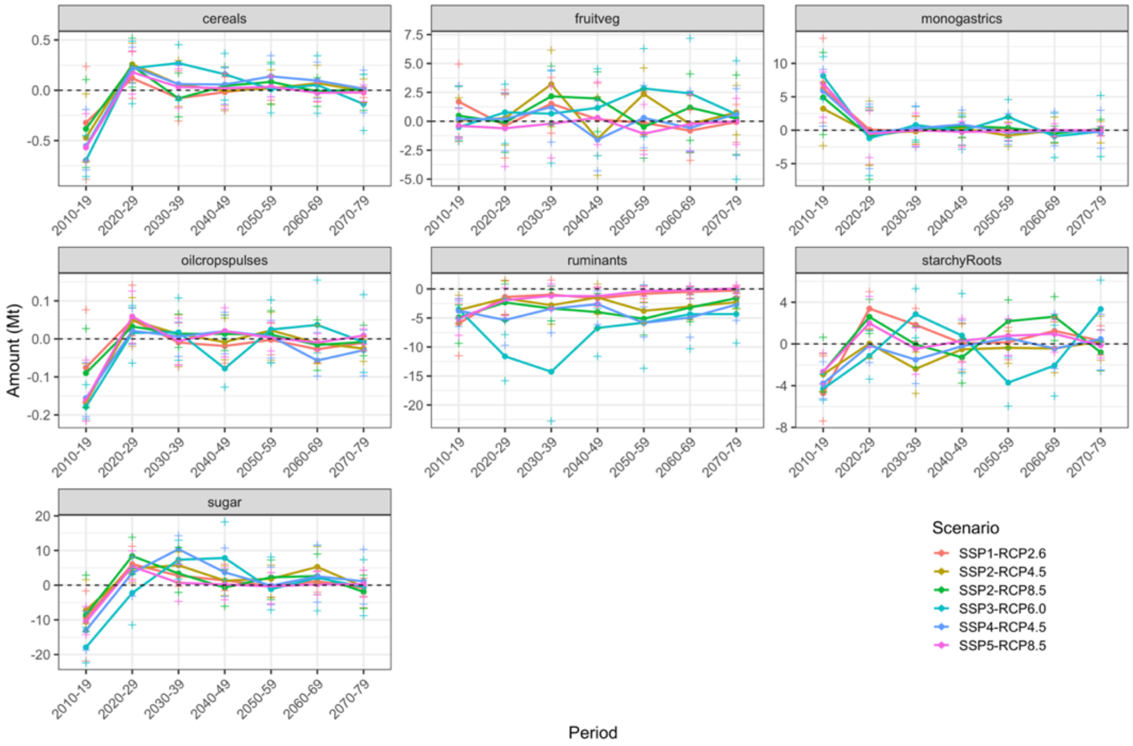

Figure S2 – Differences in global demand for food commodities from 2010 to 2080 between baseline and counterfactual scenarios. Median estimates and interquartile ranges are shown by solid lines and crosses, respectively.

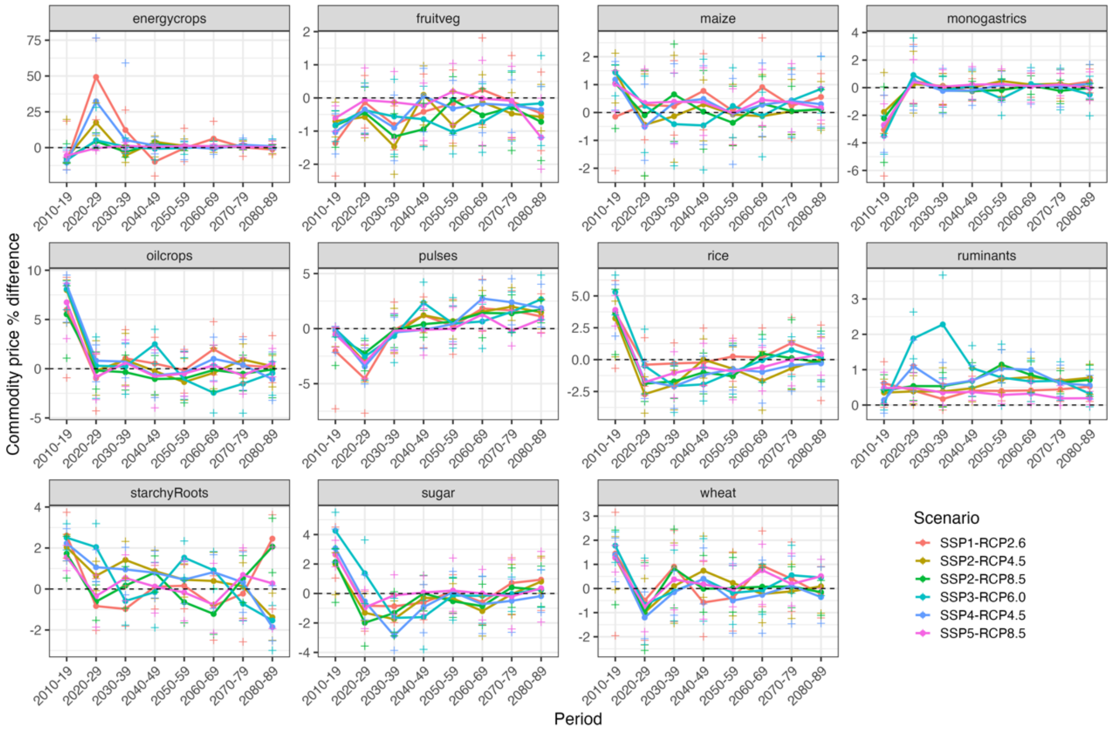

Figure S3 – Difference in commodity prices from 2010 to 2080 between baseline and counterfactual scenarios. Median estimates and interquartile ranges are shown by solid lines and crosses, respectively.

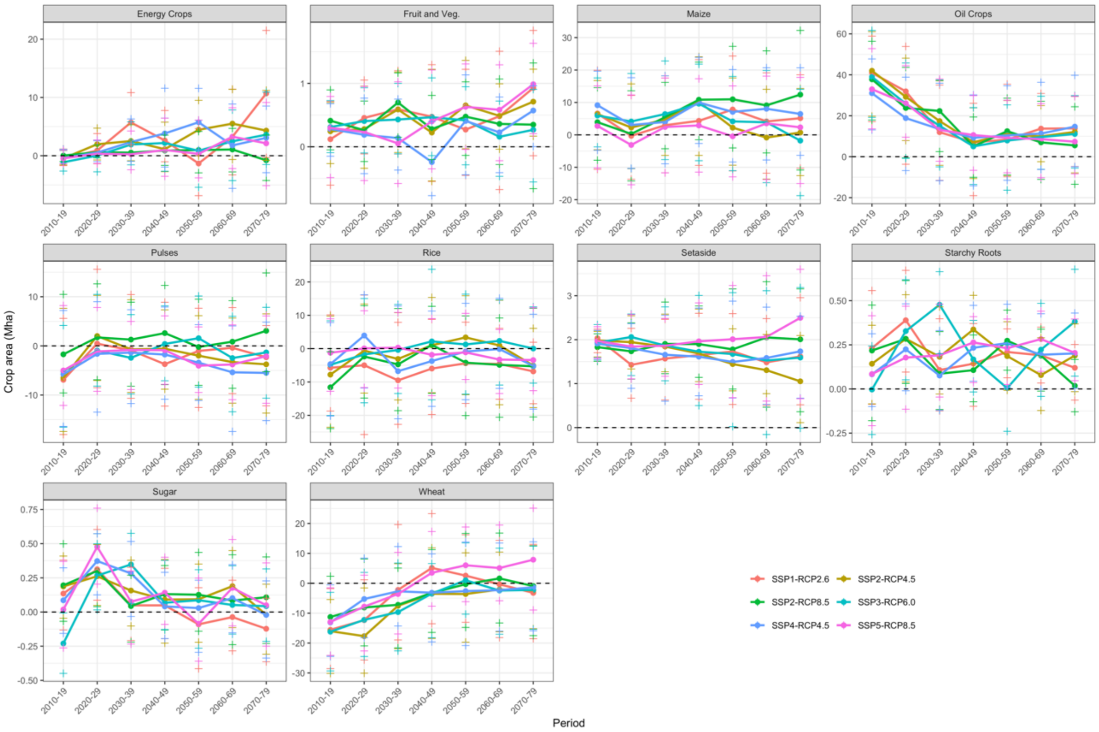

Figure S4 – Difference in crop areas from 2010 to 2080 between baseline and counterfactual scenarios. Median estimates and interquartile ranges are shown by solid lines and crosses, respectively.

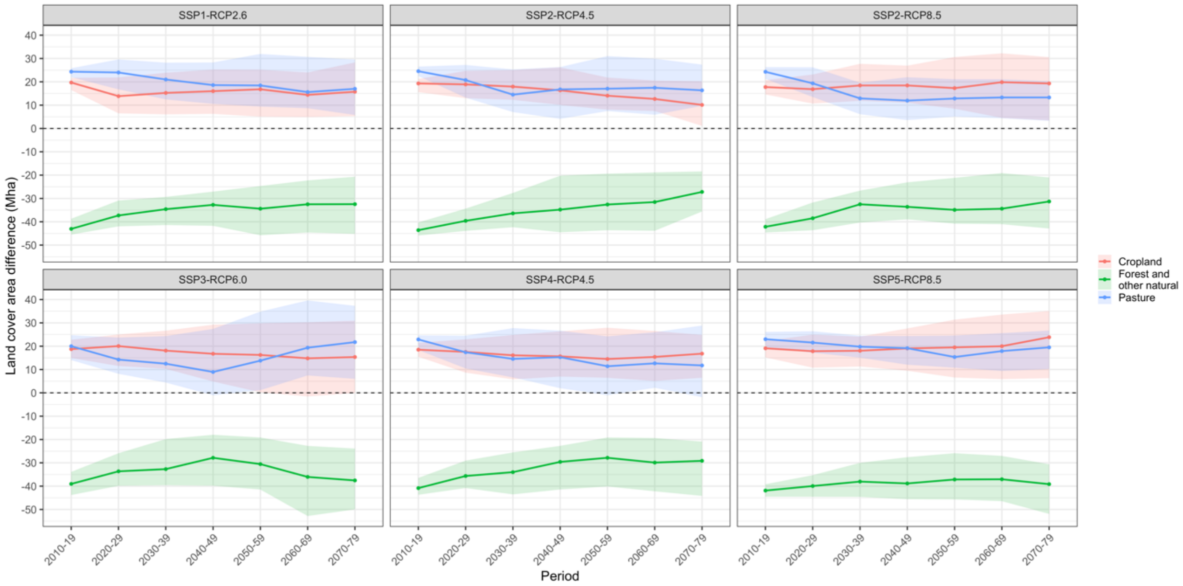

Figure S5 – Difference in global land cover from 2010 to 2080 between baseline and counterfactual scenarios. Median values are shown by solid lines and interquartile ranges are shown by shaded areas.