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Global hotspots of conversion risk from multiple crop expansion

Abstract

Habitat loss caused by agricultural expansion is a major threat to global biodiversity. A key question is which specific crops will lead future hotspots of crop conversion. We develop a spatially explicit land-rent contagion model of agricultural conversion for the top crops in terms of global area and value of production, and evaluate crop-specific threats under scenarios of current yields and closed yield gaps. We show that the ecoregions of the Western Congolian swamp forests (coconut), Northwestern Congolian lowland forests (oil palm, maize, rice), and Southern American Pacific mangroves (oil palm) present the highest birds and mammals extinctions potential. Closing yield gaps is able to reduce bird extinctions by 20% and is most effective for rice, soybean and wheat. This provides direction of which crops to be targeted by future intensification policies. Political instability appears to protect many of the remaining tropical natural habitats from crop expansion.

Keywords

Agricultural expansion, intensification, instability, agricultural rent, species extinction, scenarios

Introduction

Agricultural demand is projected to double by 2050 as a result of a growing global population and changing dietary preferences (Tilman, Balzer, Hill, & Befort, 2011). To meet this future demand, closing yield gaps via agricultural intensification has commonly been proposed (Foley et al., 2011; Tilman et al., 2001). Reducing yield gaps may however have limited effectiveness because the rate of increase in agricultural demand could outpace intensification (Ray, Mueller, West, & Foley, 2013). In addition, global agricultural demand is likely to require further cropland expansion (Tilman et al., 2011). This expansion is likely to occur within tropical countries, often at the expense of hyper-diverse forests where there are large areas of unconverted land suitable for agricultural production (Foley et al., 2011; Gibbs et al., 2010; Tilman et al., 2017).

Projections of agricultural expansion trends and resulting biodiversity impacts have revealed the potential disastrous influence of future cropland on nature (Foley et al., 2005; Phalan et al., 2013b; Tilman et al., 2011; Tilman et al., 2017; Tilman et al., 2001; Visconti et al., 2016; Visconti et al., 2011). To date, such studies have either estimated the area of land clearing required to satisfy food demand using global- or country-based approaches that were not spatially explicit (Tilman et al., 2011; Tilman et al., 2017; Tilman et al., 2001) or, among spatially explicit studies, treated new potential cropland as an aggregate without considering which specific crops pose a threat and where future conversion hotspots will occur (Hurtt et al., 2011; Phalan et al., 2013b; Visconti et al., 2016; Visconti et al., 2011). Not considering crop-specific threats leaves a critical knowledge gap since different crops have different demand, suitability distribution, yield gaps and biodiversity impacts. In addition, working at individual crop levels allows identifying crop-specific leverage points for conservation through targeted yield gap closure. Predicting crop-specific expansion is however complex. Institutional contexts and policies may play an important role in the final crop conversion process. For example, political instability and conflict could deter foreign investment and thus reduce opportunities of large-scale industrial farming (Bussm, 2010; Zhang et al., 2018).

Focusing on the most important 17 crops globally in terms of area and value of production, we: (i) identify crop-specific potential conversion hotspots under future crop-specific demands; (ii) assess mismatches between crop conversion potential and current conversion patterns to identify areas where institutional factors could be holding up rapid crop expansion; (iii) investigate the environmental and biodiversity consequences posed by potential crop expansion; and (iv) assess to what extent crop-specific agricultural intensification could deactivate these threats.

Methods

Overview

We construct a contagion von Thünen framework to model potential crop-specific threats under agricultural demands by 2050 (Fig. 1A). In the model, conversion potential is determined by both agricultural rent potential of the given crop and distance to the nearest existing distribution of the crop. We use two scenarios to assess the political and institutional constraints that may currently prevent crop expansion in areas with high expansion potential; and another two scenarios to investigate the effects of intensification on crop-specific conversion potential. We then use crop conversion potential to ascertain biodiversity hotspots, Key Biodiversity Areas (KBAs), endemic species and carbon stocks that are exposed to the highest crop-specific potential for conversion.

Modeling framework

We used the von Thünen land rent framework which predicts that the land use in each location will be allocated to uses that generate the highest agricultural rent (Angelsen, 2010). To calculate the potential rent, potential yields of the crop, crop prices, and production costs (including transport costs) were considered. Using potential yields responds to data paucity (no maps predicting what would be the actual yields in newly converted cropland are available) and the aim to estimate potential threats. Using potential yields in newly converted land implies assuming that yield gaps are closed instantaneously during crop conversion. The distance separating the land cell from the market was determined to assess transport costs whereby increasing market distance leads to higher cost and thus lowers agricultural rent. The framework was used to investigate future cropland distribution patterns by comparing the potential rent (R_0) of each crop *i* for each land cell *j*. The model allocates the crop with the highest potential rent to each location iteratively, provided the projected demand for the crop has not yet been met. Agricultural rents were calculated as:

$$R_{0ij} = p_i y_{ij} - c_{ij}$$

where *p* is the crop price ($/ton), *y* is the potential yield (ton/ha) and *c* the production costs ($/ha).

Agricultural rent is however not the only factor that determines crop conversion potential. Other factors such as cultural preference for certain crops, cultivation know-how, accessibility to labor and ease of management are not considered in the von Thünen framework. In an attempt to capture these factors, we expanded the von Thünen model into a “contagion von Thünen model” to account for potential spatial autocorrelation and the influence of pre-existing crops being grown on neighboring land. The land rent model was modified as follows:

$$R_{ij} = R_{0ij} + 1 - e^{ad}$$

where R_0 is the agricultural rent from the traditional von Thünen model ($/ha), *d* the distance to the nearest similar crop (km) and *a* is a parameter to be estimated to account for the decay in the influence of existing crops on the type of crop used in the newly converted land as distance grows which is translated in the model as an additional cost penalty.

We fitted parameter *a* through maximum likelihood. Cropland conversion from 2000 to 2014 (Climate Change Initiative Land Cover Team, 2017) was coded as one and not conversion as zero. The conversion of each cell was assumed to follow a Bernoulli distribution. The log-likelihood function was:

$$L(p) = \log\left[\prod_{i=1}^{N} p^{x_i}(1-p)^{(1-x_i)}\right]$$

where p is the prediction of cropland conversion by the model and x is the observed cropland conversion in each cell (*Supporting Methods*). When fitting the parameter in the model, we ran the model considering all 17 crops and produced individual crop expansion patterns from 2000 to 2014. However, due to data paucity, we could not parameterize the model using actual expansion patterns of individual crops but against overall cropland expansion.

Data collection

We compiled spatial information on global land cover and factors that could influence cropland expansion through a 0.25° global fishnet (around 28km at the equator) (Table S1). All spatial analyses were conducted in in ArcMap v10.2 (Environmental Systems Research Institute, 2013). Values were exported to R v3.2.1 (R Core Team, 2017) for analysis. The models were run from 2015-2050 for 208 countries. All monetary values (e.g. wage, price) were converted to $USD of 2005.

We focused on 17 agricultural products including banana, beans, cassava, cocoa, coconut, coffee, cotton, cowpea, groundnut, maize, millet, oil palm, rice, sorghum, soybean, sugarcane, and wheat. They were selected based on their economic importance and area of production (Leff, Ramankutty, & Foley, 2004; Phalan et al., 2013a). In total, they represented around 65% of total global crop production (FAOSTAT, 2014b). The global land cover used to identify initial and final areas of cropland in the parameterization process was from the Climate Change Initiative Land Cover (CCI_LC) map series for both year 2000 and year 2014 (Climate Change Initiative Land Cover Team, 2017). We classified land cover types into three categories: cropland, non-cropland land available for conversion, and unsuitable land. Non-cropland available for conversion included tree covered areas, grasslands, wetlands, shrublands, and sparse vegetation. Unsuitable land included urban areas, bare areas, water bodies, and snow and ice (Table S1). Before running the multi-crop expansion model, we removed locations covered with existing cropland and unsuitable land. There were 103,776 cells remaining after the exclusion on the map, spanning 25 different land-cover types (Table S1).

To calculate potential agricultural rents, the global yield data of each crop were obtained from potential rain-fed yield global maps (International Institute for Applied Systems Analysis, 2015). These potential yield maps have been developed using the Global Agro-Ecological Zones model of the Food and Agriculture Organization and the International Institute of Applied Systems Analysis (Fischer et al., 2012). Potential yields are obtained by the model using temperature, radiation and moisture regimes across the globe. They also include, among others, the length of growth of cycle of the crop, maximum yield of photosynthesis given current temperatures, leaf area index, crop water requirements and response of the crop to water stress (Fischer et al., 2012). Although the model potential yield predictions are available under rain-fed and irrigation conditions, we assumed, conservatively that the crops could only be grown under rain-fed conditions.

Price data were the annual producer prices of each crop from the Food and Agriculture Organization statistical database (FAOSTAT, 2014a). We considered only data from the last ten years (2003–2013) and the price of each crop in a given country was taken to be the average price to account for price fluctuations. We assigned world averages to countries without FAOSTAT data. There were two key types of production costs: labor costs and transport costs (*trans*). We calculated labor cost per country for each of the 17 crops as the product of the daily wage and number of labor-days required to produce one hectare of a given crop. We obtained wage data for the agricultural sector of each country from the International Labor Organization statistical database (ILOSTAT, 2014) and estimated the average labor-days (Table S2). We calculated transport cost for each crop i in each cell j as:

$$trans_{ij} = y_{ij} a_j f_i$$

where y is the potential yield (ton/ha), a the accessibility (mins) and f the freight rate ($/ton·minutes). Freight rate was comprised of drivers' wages and diesel fuel cost. Gasoline prices

($/liter) for each country were taken from the World Bank database (The World Bank, 2014). The fuel cost of transporting a given crop at a particular location was then calculated by considering truck speed, location accessibility, truck capacity, crop density and truck fuel consumption (Murray & Boevey, 1981). Location accessibility data were estimated as the time required to access the nearest large cities (Nelson, 2008). To calculate drivers' wages ($/hr), the hourly wage was multiplied by the accessibility (in hours) of the location in each country for two-way trips. We could not find global maps of fertilization utilization and machinery utilization and costs for all the crops and decided not to include those costs.

To provide a starting point for the model, we used the production volume of the 17 crops from FAOSTAT (FAOSTAT, 2014b) for the year 2013. To project future crop demand, the world production quantity of each crop was used as a proxy of global demand for that crop. For simplicity, we assumed production quantity to be a function of the global population, and we fitted crop production data from 1961–2013 against world population data for the same time period using linear regressions (FAOSTAT, 2014b; UN Population Division, 2004). We considered a linear relationship or a saturating relationship (by log transforming the dependent variable) and chose the model with the lowest Akaike information criterion. For each crop, we extrapolated the regression line to obtain the agricultural demand for the projected world population up to year 2050 (Table S3). The demand model of oil palm was the only crop in which a log-transformation improved the fit. The predicted global demand for most crops was remarkably similar to the Food and Agriculture Organization food and agriculture projections (FAO, 2019) barring for oil palm that had a higher projected demand in our case due to the log-transformation.

To get distance of each location to the nearest cropland area where the same crop was grown, we selected existing cropland patches larger than 7,400 ha from the actual yield maps of individual crops (Monfreda, Ramankutty, & Foley, 2008; Ramankutty, Evan, Monfreda, & Foley, 2008). Actual yield was used as a proxy for the individual crop being present there. We assumed that if new crop would be grown away from cropland with patch size above 7,400 ha of its type, additional costs other than those captured by conventional agricultural rent would occur (Strano et al., 2017).

We also considered the cultivation history of individual crops when projecting their future expansion patterns. This served a similar function as the contagion component in our crop expansion model and accounted for the cultural or historical preference of certain crops. Historical crop growth was estimated from CCI-LC maps across 2000-2014 where we found that more than 99% of large cropland patches (above 7400 ha) had expanded less than 66km away from existing patches. We therefore used a 66km buffer around each location to calculate each crop's production quantity based on the actual yield data and existing harvest fraction data (Monfreda et al., 2008; Ramankutty et al., 2008) and did not allow crop conversion beyond 66km of existing and projected cropland.

We obtained the distribution of protected areas from the World Database on Protected Areas and limited protected areas where IUCN categories had been assigned (UNEP-WCMC, 2016). We used the global biomass density distribution map produced by the EU FP7 GEOCARBON project to estimate potential carbon emissions due to cropland expansion (Avitabile et al., 2014). We also overlaid the predicted cropland expansion with the KBAs from the World Database of Key Biodiversity Areas (BirdLife International, 2017) and the biodiversity hotspots from the Critical Ecosystem Partnership Fund (Noss et al., 2015).

Multi-crop expansion model

The multi-crop expansion model identified areas of potential cropland expansion based on current production, agricultural demand, and potential agricultural rents at each cell (Table S4). In each year from 2015-2050, if there was a gap between production and demand, the model would first convert the cell with the highest agricultural rent. Then the ranked cells according to agricultural rent would be converted in turn until crop demand could be satisfied for every crop (see *Supporting Methods* for a description of the model simulation procedure). At each cell, the crop that presented the highest agricultural rent would outbid the other crops and be allocated.

Scenarios to assess the influence of institutional factors

We used maps of actual historical cropland expansion from 2000 to 2014 to compare our model identification of high crop conversion potential areas during that same time period. We figured out the areas with greatest mismatch to identify potentially ongoing political and institutional contexts that could be preventing the crops from realizing their potential.

To assess the impacts of political instability, agricultural policies preventing cropland expansion and political regimes on cropland conversion, we further considered two scenarios to investigate the mismatches between potential and actual expansion trends from year 2000 to 2014, using the multi-crop expansion model. In the first scenario, we penalized countries with high political instability or corruption by lowering their agricultural rents. These countries were Angola, Central Africa Republic, China, Congo, Democratic Republic of Congo, El Salvador, Guatemala, Guinea, Guinea-Bissau, Haiti, Honduras, Laos, Malawi, Myanmar, Nepal, Uganda, and Venezuela. In the second scenario, we penalized countries (China, Cuba, and North Korea) with political regimes that may affect future cropland conversion also through lowering their agricultural rents. For example, the Grains for Green program in China aiming at afforestation may greatly reduce probabilities of new cropland conversion. In Cuba and North Korea, foreign investment opportunities are low and this might slow down cropland expansion. We estimated the most suitable penalization value through comparing the maximum likelihood of different possible values (similar as fitting parameter "a" in the multi-crop expansion model). We found that when agricultural rents of these countries were lowered by $4,800 per hectare, the likelihood of the model was maximized.

Impacts on biodiversity and ecosystems

We overlaid the identified areas with high crop conversion potential with biodiversity hotspot and KBAs distribution maps to investigate the potential impacts that each crop would pose to areas with high biodiversity and conservation value if their potential were realized. We also estimated potential biomass loss through overlaying the biomass density map with the projected cropland expansion maps. After that, we calculated the resultant cost of carbon emissions in 2007 USD with a carbon fraction of biomass ratio (Feldpausch, Rondon, Fernandes, Riha, & Wandelli, 2014) and carbon social prices, which were based on the White House estimates (25USD/ton) (United States Government, 2016) (see *Supporting Methods*).

We estimated possible endemic species extinction rates caused by projected land use change according to a countryside species-area relationship (SAR) model (Chaudhary, Verones, de Baan, & Hellweg, 2015; de Baan, Mutel, Curran, Hellweg, & Koellner, 2013).

$$S_{lost,g,e} = S_{org,g,e}\left[1-\left(\frac{A_{new,e}+\sum_{l=1}^{L} h_{g,l,e}\times A_{l,e}}{A_{org,e}}\right)^{z_e}\right]$$

where $S_{lost,\,g,\,e}$ is the predicted number of species loss of taxa *g* due to projected cropland expansion in ecoregion *e*, $S_{org,\,g,\,e}$ is the original number of species occurring in natural habitat area $A_{org,e}$ in the ecoregion, $A_{new,e}$ is the remaining area of natural habitat after land use change, $A_{l,e}$ is the updated area of each land use type *l* in each ecoregion, z_e is a constant for each ecoregion, and $h_{g,l,e}$ is the affinity of each taxa *g* for land use type *l* in ecoregion *e*, which was calculated as,

$$h_{g,l,e} = (1-CF_{loc,g,le})^{1/z_e}$$

where $CF_{loc,g,le}$ is the local land occupation characterization factor, which measures the relative difference between the species richness in land use type *l* and the natural reference area of the same ecoregion *e*.

Our data on $CF_{loc,g,le}$ and z_e were from previous studies (Chaudhary et al., 2015; de Baan et al., 2013). We used a land use map (Climate Change Initiative Land Cover Team, 2017) to get land use distributions before and then added the areas with high potential for crop conversion. Endemic species richness data for each ecoregion were obtained from WildFinder (World Wildlife Fund, 2006) and ecoregion distribution data were from the World Wildlife Fund (Olson et al., 2001). We limited this extinction rate estimation only to birds and mammals due to data paucity for other taxa.

Scenarios to assess the effects of intensification

We used two scenarios to assess how agricultural intensification could mitigate threats to the environment and biodiversity.

Baseline scenario: no cropland expansion into protected areas were permitted and no intensification in crop production was considered.

Intensification scenario: no cropland expansion into protected areas was permitted. However, intensification in existing cropland in each year was possible and yield gaps were closed before further crop expansion was allowed. If any crop had unsatisfied demand after agricultural intensification was completed in all the existing crop distribution, cropland expansion occurred. Intensification was done iteratively following a rank for each cell's potential agricultural rent for each specific crop.

Results

Combining all crops, hotspots of conversion potential were in China and Africa, especially Congo, Democratic Republic of the Congo, Chad, Angola and Ethiopia, followed by Central and South American, including Colombia, Venezuela and Peru, and South and Southeast Asia, particularly Nepal and Sulawesi (Indonesia). Besides China and Nepal, there were no hotspots of conversion potential in the sub-tropical or temperate zones (Fig. 2, S1 and Table S5).

Scenarios to assess the influence of institutional factors

The comparison of areas predicted to have high conversion potential from 2000-14 using the multi-crop model presented mismatches with the areas of contemporary cropland expansion (Fig. S2, S3, S4 and S5). These areas of discrepancy were mostly in Venezuela, Central African countries, including

Congo, Central African Republic, Chad and Angola, and Myanmar and Laos. On the other hand, Brazil, Argentina, Kazakhstan and Australia presented larger actual crop conversion than crop conversion potential.

The two scenarios of institutional and policy constraints appeared to explain the mismatches between projected high conversion potential and actual cropland expansion areas. In the scenarios limiting conversion in countries for political reasons, cropland expansion was projected instead to occur more in Southeast Asian countries like Cambodia, Malaysia, and Indonesia and be more prevalent in South American countries, such as Bolivia and Brazil, improving the fit of the model (Figures S4, S5).

Scenarios to assess the effects of intensification

In the baseline scenario (no yield improvements), 260 Mha of land had high crop conversion potential under 2050 agricultural demands. About 80% of this area occurs on forested areas. Realizing this crop conversion potential would lead to carbon dioxide (CO_2) emissions costing US$120 billion (Fig. 1). Cotton, maize, oil palm, rice, soybean, sugarcane, and wheat presented the largest crop conversion potential, collectively accounting for more than 92% of the area with potential for conversion. Oil palm and wheat accounted for 46% of the crop expansion potential alone (Fig. 2, S1, and Table 1).

Among the 36 biodiversity hotspots, Sundaland and Tumbes-Chocó-Magdalena (mostly driven by oil palm) were two of the top five hotspots with the highest crop conversion potential across all scenarios (Fig. S6). Among the 14,936 KBAs studied, those with more than 50% habitat conversion potential were concentrated in Asia and Africa (Table S6 list the KBAs under highest threat).

Among the taxa considered, birds were the most severely affected (Fig. 1). The highest number of predicted global extinctions was concentrated in the ecoregions of the Western Congolian swamp forests (Congo and DRC, with high threats from coconut), Northwestern Congolian lowland forests

(Gabon, Congo, Cameroon, and Central African Republic, with threats from oil palm, maize and rice), and Southern American Pacific mangroves (Panama, Colombia, and Ecuador with threats from oil palm). An estimated 17% of endemic bird species in Western Congolian swamp forests would become extinct under the baseline scenario. For mammals, they were most seriously and commonly affected in the Northwestern Congolian lowland forests, where ~4% of endemic mammal species of the ecoregion were projected to go extinct under the baseline scenario (Fig. 3, S7–S11).

In the intensification scenario, total cropland expansion potential dropped to 205 million hectares (27% drop from the baseline scenario) with potential CO_2 emissions costing $99 billion (Fig. 1). Compared to the baseline scenario, intensification drove crop expansion potential away from the tropical forest belt towards Turkey, China, Myanmar, Angola, South Africa, as well as Central African Republic. The potential threats by rice, soybean and wheat were greatly reduced, as a result of demand satisfaction by increased yields (Fig. S1). Land intensification also reduced the impacts of cropland expansion potential on biodiversity. About 20% and 6% of bird and mammal global species extinctions would be prevented and 35 fewer KBAs would be under crop conversion potential with land intensification (Fig. 1, Table S6).

Discussion

Crop expansion threatens many of the remaining large extents of natural habitats in the tropics: northern fringes of the Amazon Basin, Central Africa, Myanmar and Laos. Institutional instability appears a key factor that protects these remaining natural habitats from conversion. This is reflected in our results through discrepancies between observed contemporary trends in crop expansion (Climate Change Initiative Land Cover Team, 2017) and potential for crop conversion. For instance, the Congo Basin has high cultivation potential for many crops facing an increase in demand, such as rice, oil palm, and coconut, and indeed the investment of international oil palm companies in the Congo Basin is rapidly increasing (Wich et al., 2014). Yet the current low extent of exploitation in the Congo Basin is due to political instability (Phalan et al., 2013a). Similar discrepancies occur in Angola and Venezuela which present political instability and risks that can deter international investment (Fernandes, Jimenez, Kraak, & Tsagdis, 2019; Zhang et al., 2018). Other large areas of discrepancy are in China which could respond to national policies discouraging cropland expansion. These are chiefly exemplified by the Grains for Green project, the greatest reforestation project worldwide (Hua et al., 2016).

The results showed that land intensification could decrease cropland conversion potential by around 25% and halve bird extinctions, thus substantially reducing the potential impacts on biodiversity and CO_2 emissions. Although previous studies have suggested that improved crop yields can reduce required cropland and could also spare land in the future (Byerlee, Stevenson, & Villoria, 2014). increased land returns from intensification could incentivize more cropland expansion (Phelps, Carrasco, Webb, Koh, & Pascual, 2013). One possible strategy to deal with this is through certification schemes that promote sustainable crop production at all levels or the use of zonation (Phalan et al., 2016). That intensification will be beneficial for biodiversity holds true only if no other externalities and threats are posed on biodiversity from increasing yields. Species-specific responses to land intensification are however poorly studied and intensification could be highly detrimental for biodiversity [e.g. recent research shows that use of insecticides affects common birds species (Eng, Stutchbury, & Morrissey, 2019)] and further research would be needed to fully estimate the implications of intensification (Byerlee et al., 2014).

We found some leverage points for biodiversity protection though targeted yield gap closures. Rice, soybean, and wheat where the crops where yield gap closure can prevent most cropland expansion. These crops’ current distributions occupy a wide latitudinal range with relatively low production yields while having high potential to lead conversion hotspots in the future. Their distribution thus allows sparing tropical conversion through intensification in temperate regions, something that is not possible with tropical crops such as oil palm, coffee or cocoa.

Our analyses, although able to provide insights on expansion potential across multiple crops, present multiple limitations. Due to lack of maps, we assumed that yields after cropland expansion would follow potential yields. The extent to which yield gaps will be closed and how fast this will happen is however challenging to ascertain (Tilman et al., 2011). One fundamental assumption of the model is that cropland allocation is market-driven where individual actors behave rationally with perfect information to maximize profits. The effects of other institutional factors such as political instability, government intervention, trade barriers, food security policies in each country (prioritizing national production over international trade) were indirectly tested after the simulations through two comparative scenarios. The implications are that our analyses are restricted to identify areas of high crop conversion potential but not able to predict when that potential will be realized—which depends on punctuated changes in policies that are very hard to predict.

Further assumptions are that, by using a contagion model, crops cannot perform large jumps to areas where they are not currently grown. This assumption, that should be able to capture the majority of crop conversion dynamics, may not be realistic when large agri-business with capacity to reproduce the know-how to grow a new crop in, for instance, a new continent, decide to invest there. Predicting these long jumps is however remarkably difficult and should be an area of further research. Other simplification of the model is that we did not incorporate potential yield changes due to climate change, which could allow expansion at the fringes of existing cropland (Cohn, VanWey, Spera, & Mustard, 2016). Finally, due to data paucity at the species level, the species-area relationship was used to estimate species extinctions. Although widely-used, this approach is known to overestimate extinction probabilities (He & Hubbell, 2011).

Conclusion

Our results show that most of the remaining tropical natural habitat areas with high biodiversity have high potential for crop conversion. Political instability across tropical nations and reforestation policies in China seem to be preventing this potential crop conversion to be realized. Agricultural intensification, on the other hand, shows potential to substantially reduce impacts of crop conversion on biodiversity. We identify rice, wheat and soybean as crops that should be prioritized for yield gap closure. They have large potential to mitigate of future crop conversion on the increasingly scarce remaining tropical natural habitats.

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Data availability

All data used for the analyses are publicly available under the referenced sources.

Code availability

Modelling code is available from the authors upon request.

Figures

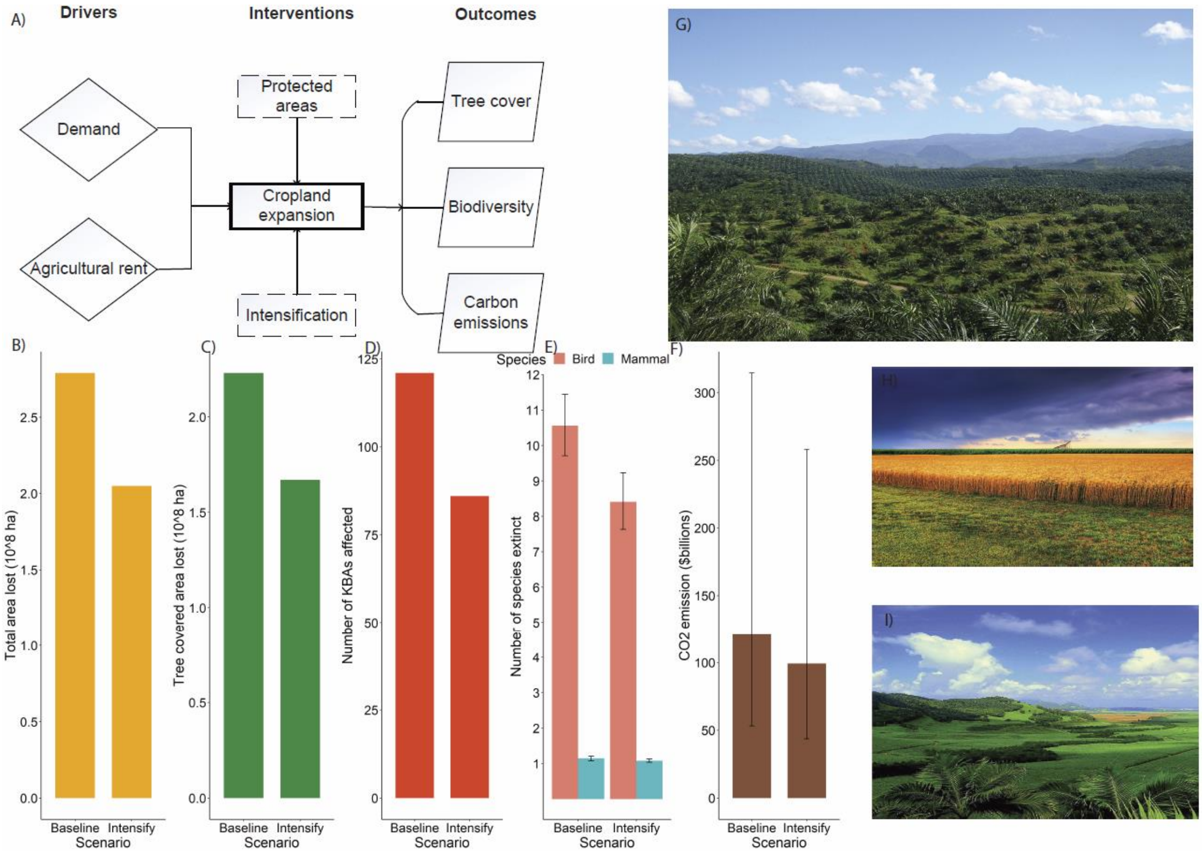

Figure 1. Modeling framework and results. A) cropland expansion potential modeling framework; B), C), D), E) and F) impacts of projected cropland expansion up to year 2050 on: natural area lost, deforested area, number of KBAs affected (>50% cropland conversion), projected endemic species extinction and CO2 emissions in monetary terms respectively; G) and H) oil palm and wheat plantations, crops with high potential of natural habitat conversion. Scenario 1: baseline, no cropland expansion into protected areas were permitted and no intensification. Scenario 2: intensification, no cropland expansion into protected areas was permitted and intensification in existing cropland was carried out first.

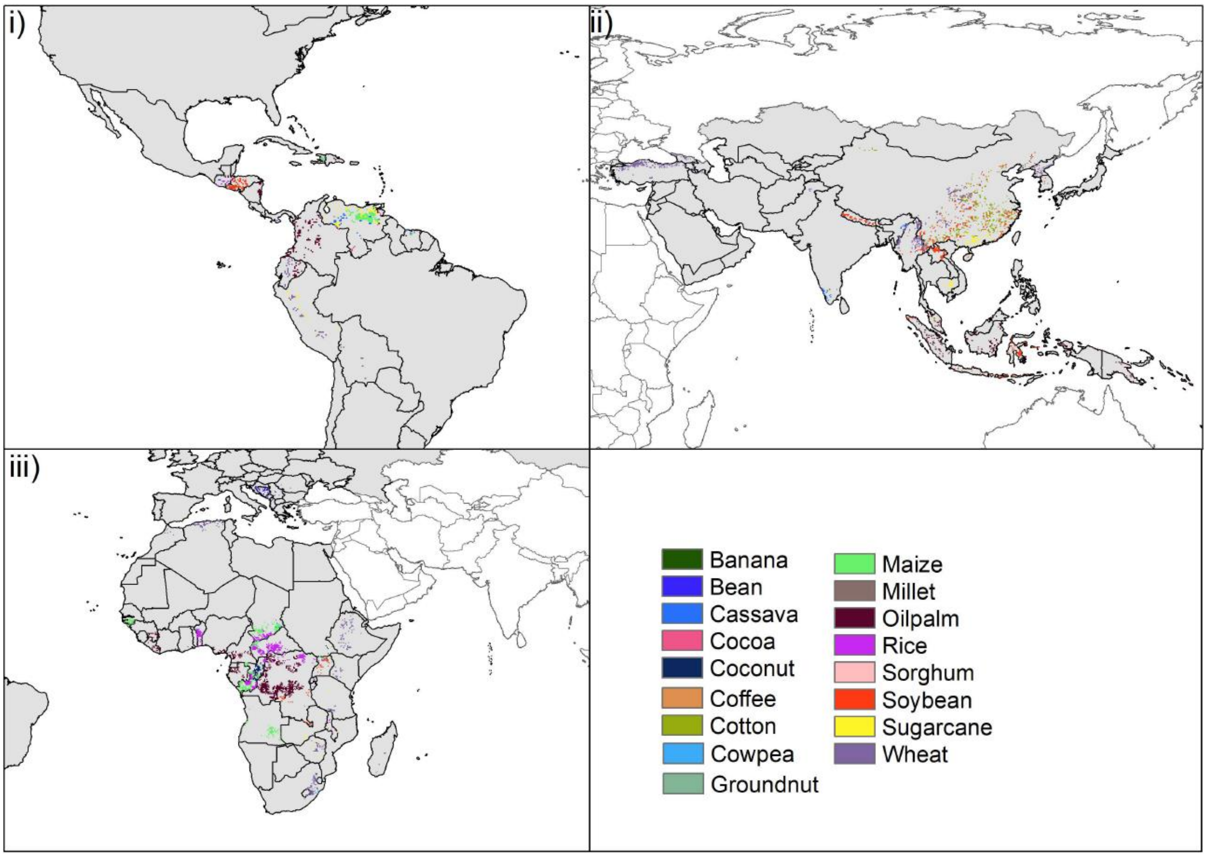

Figure 2. Crop-specific conversion potential for individual crops under the baseline scenario for crop demand by 2050.

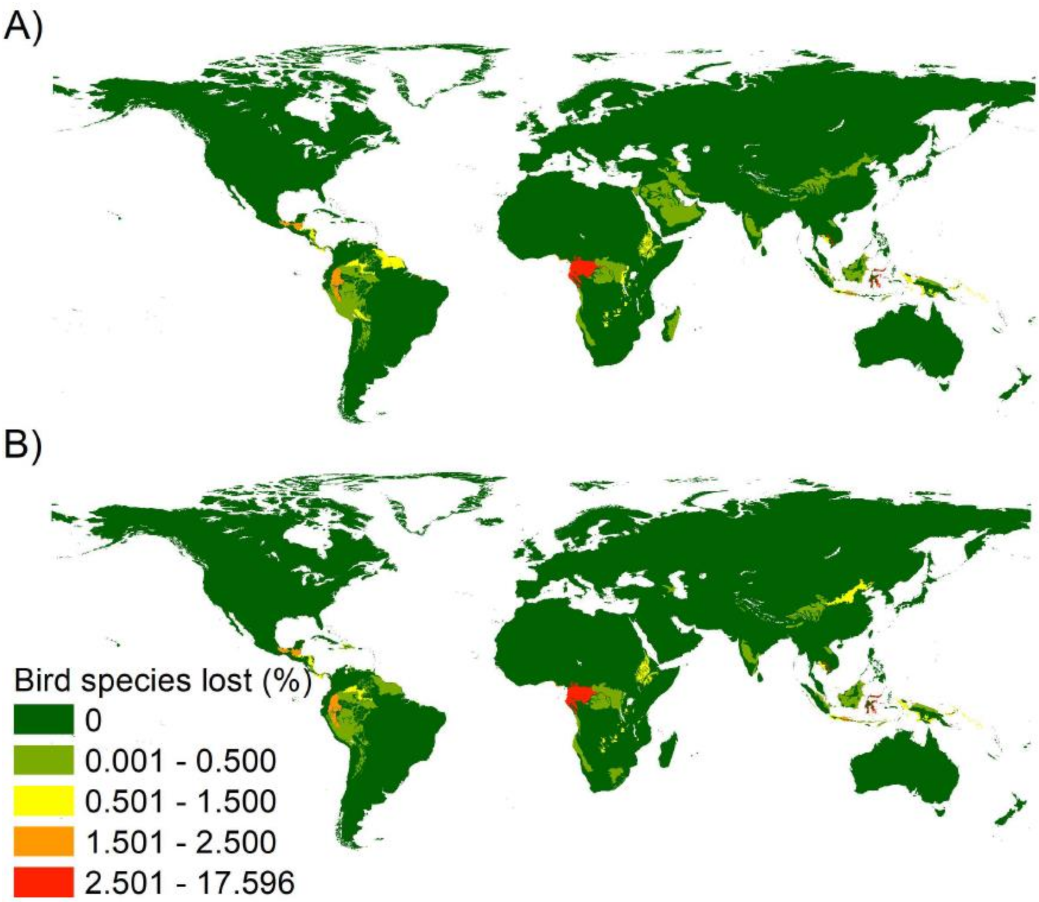

Fig. 3. Percentage of endemic bird species loss in each ecoregion due to cropland expansion potential under A) baseline scenario; and B) intensification scenario.

Tables

Table 1. Area converted to each crop in million hectares and its proportion of expanded cropland in the baseline scenario, and intensification scenario.

Crop	area	proportion	area	proportion
	baseline scenario		intensification scenario	
Banana	1.060	0.004	1.051	0.005
Bean	1.922	0.007	0.000	0.000
Cassava	5.594	0.020	5.671	0.028
Cocoa	0.848	0.003	0.771	0.004
Coconut	5.653	0.020	5.730	0.028
Coffee	1.290	0.005	1.080	0.005
Cotton	21.318	0.076	18.924	0.092
Cowpea	0.415	0.001	0.135	0.001
Groundnut	3.885	0.014	3.838	0.019
Maize	28.481	0.102	25.440	0.124
Millet	1.767	0.006	0.000	0.000
Oil palm	75.321	0.270	73.240	0.358
Rice	28.311	0.101	7.837	0.038
Sorghum	1.214	0.004	0.000	0.000
Soybean	35.611	0.128	22.586	0.110
Sugarcane	13.250	0.048	13.095	0.064
Wheat	53.003	0.190	25.290	0.124