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Predicting 21st century global agricultural land use with a spatially and temporally explicit regression-based model

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A B S T R A C T

The extensive alteration of the earth's land cover during the anthropocene had widespread, and in some cases unknown, effects on terrestrial and atmospheric conditions and processes. Predicting future changes to the earth system therefore mandate a future-predicting framework of land use dynamics. However while future-predicting earth surface and atmospheric models tend to explicitly incorporate projected climatic conditions they all but ignore or overly simplify land use dynamics. As most surface and atmosphere dynamics models use gridded input datasets, and land use is a highly spatially-dynamic phenomena, a need clearly arise for spatially explicit representation of future land use dynamics. While a number of such datasets exists at regional and country scales, no fully gridded future-predicting global land use model and database has been reported to date. Here we present the Global Land Use Dynamics Model (GLUDM), a gridded and temporally explicit agricultural land use predictor. GLUDM calculates the relative area of a land use category (e.g. cropland) in each grid-cell by generating unique regression coefficients in each grid-cell based on local historic trends and global population dynamics. Spatial expansions or abandonment of agricultural land is simulated by propagating excesses or deficiencies in agricultural areas between neighboring grid-cells. This spatial connectivity is restricted by topographic, latitudinal and urban characteristics. A validation analysis shows that GLUDM corresponds well to observed land use distribution. GLUDM-predicted global cropland area dynamics between 2005 and 2100 are described herein. Globally, 18% increase in cropland area is predicted between 2005 and 2050 which corresponds very well to previous estimations. Following 2050, a general decrease in cropland area is predicted. The results reveal new insights about global cropland dynamics, demonstrating, for example, that changes in its spatial distribution will be highly heterogeneous, at both micro and macro scales, in some locations worldwide.

1. Introduction

Over the last 300 years humans have greatly altered the natural environment to meet demands for food, fiber, and settlement. The pre-existing ecosystems have been continually relegated to ever shrinking marginal undeveloped and managed areas. As a result the world's natural land cover has been substantially modified. It has been estimated that as much as 50 percent of the Earth's land surface has its biological production completely dominated by humans (Vitousek, Mooney, Lubchenco, & Melillo, 1997). Similarly, Ellis, Goldewijk, Siebert, Lightman, and Ramankutty (2010) found that 39 percent of the earth's ice-free land area had either been converted to agriculture or to urban areas. This modification of natural systems has disrupted a number of important biogeochemical cycles such as the carbon and nitrogen cycles. This has led to increased levels of greenhouse gases, a decline in the health of aquatic ecosystems, and has altered precipitation.

The primary driver of this expansion is the expanding human population (Doos & Shaw, 1999). From 1900 to 2000 the population of the earth experienced a 400 percent increase. While the growth in human biomass is itself a factor, the resulting increase in natural resource consumption to feed, cloth, and house a population of this multitude has had a far greater impact on the environment. While impoundments, mining operations, and forestry make significant changes to the landscape, nothing has altered the natural landscape as much as conversion to agriculture. Over the last 300 years agricultural expansion has resulted in a global net loss of between 8 and 11 million km^2 of forestland (Foley, DeFries, Asner, Barford, &

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Bonan, 2005). Conversion to agriculture has lead to increased runoff, soil erosion, denitrification, desertification, the extinction and endangerment of many species, and an altered atmospheric composition (Tilman, 1998; Foley et al., 2005).

Scientists have long understood the consequences of conversion to agricultural and sought accurate estimates of the global amount of land under agricultural production. Until the 1960's this was impossible as many nations were unable to inventory the amount of agricultural land. The Food and Agriculture Organization (FAO) of the United Nations began keeping detailed records of the amount of agricultural land in each of its member nations in the 1960's (FAO, 2013). By the 1990's the global coverage of IR satellite imagery and the greater availability of agricultural data increased the accuracy and ease of making these estimates. Ramankutty and Foley (1999) developed a comprehensive map of the extent of modern agriculture by combining remotely sensed data with cropland inventories where available. Using recent trends in agricultural development they were able to use a simple land use allocation model and run the model in reverse to the 1700's using available land use data as a model constraint. The HYDE database, using a similar approach to Ramankutty and Foley (1999), was developed to test the IMAGE 2 climate change model and was able to model land use back to 10,000 B.C. (Goldewijk, Beusen, van Drecht, & de Vos, 2010).

Global and continental scale numerical models are increasingly being developed and used for predicting current and future atmospheric, biospheric, hydrospheric and lithospheric conditions and fluxes. As most of these models use gridded representation and land use is often an important parameter, predicting future land use dynamics at global scale on a gridded surface is an important and timely undertaking. For example, the WBMsed model (Cohen, Kettner, Syvitski, & Fekete, 2013) is a gridded model that predicts daily water, sediment and nutrients flux in global rivers (Cohen, Kettner, & Syvitski, 2014). The model can be used to predict 21st century fluxes using future-predicted climatic datasets form a suite of GCMs (General Circulation Models) outputs. As land use is a key parameter in water, sediment and nutrient input to river systems, developing a spatially and temporally explicit land use input dataset would be instrumental for reliably predicting these fluxes into the future.

Based on two independent review papers (Heistermann, Muller, & Ronneberger, 2006; Schmitz et al., 2014) we conclude that, to date, no future-predicting, global, fully gridded and temporally explicit land use dynamics predictions have been published. CLUE (Veldkamp & Fresco, 1996) is a process based modeling framework that allows the user to develop spatially explicit future land use dataset based on multiple scenarios. However this model works only at the regional scale and requires numerous variables for which global data is not available. If the data was available this approach is still impracticable for global scale modeling as data would be collected within political units and the grid cells would overlap international boundaries. Thus economic policies, political decisions, and other variables would not be applicable. Other factors such as a global set of detailed soil types, types of crops grown, available water supply, and agricultural practices are difficult or impossible to obtain even at regional scales. This necessitates significant abstraction if agricultural land use is to be modeled at the global scale using a spatially explicit gridded model.

Despite these difficulties modeling land use, using a gridded structure can be achieved by focusing on the one variable that has the most influence on determining agricultural land use. This variable should be easy to obtain and one that is universally understand to influence the amount of agricultural land necessary. This variable is global population. While this may not be the single most important variable at a sub global scale it is appropriate to use at a global scale given our globalized agricultural system.

In this paper we describe the theoretical and algorithmic framework of the Global Land Use Dynamics Model (GLUDM), present validation results and discuss future agricultural land use dynamics, focusing on 21st century changes in cropland.

2. Methods

2.1. Theoretical framework

Historically, the most significant controlling factor on global agricultural extent has been human population (Doos & Shaw, 1999). While in pre-industrial times the population of each country or region controlled the local extent of agriculture, in the current industrialized economy global population seems to be the main control on the amount of global agricultural land (Trostle, 2008). Thus as global population increases the total amount of agricultural production must also increase.

Another major factor is the technology used in agricultural production. Advancements in agricultural technologies mean that increasing global population will require a relatively smaller increase in agricultural lands (Heistermann et al., 2006). The global standard of living is another important factor. Wealthy societies have a higher caloric intake than poorer societies, requiring a greater agricultural area to sustain them. Economic factors, water availability and human decision making controls which types of crops is planted with less productive crops requiring a greater amount of agricultural land to sustain the same number of people (Heistermann et al., 2006). An absolute constraint on the spatial extent of agricultural land is the environmental variables acting at a given point in space and time. These includes factor such as latitude, altitude, and climate. However environmental constraints can change overtime in response to human impacts or advances in technology.

The question now becomes which of these variables are easily available and are applicable at the global scale. Estimates of population are readily available from the aforementioned HYDE dataset. The environmental variables latitude and longitude are also easy to implement. However the other variables, described above, are either unavailable or inapplicable at the global level. A way to account for these variables implicitly is through the development of regression equations based upon the principle driver of agricultural development, population.

Creating a global regression equation is illogical and will convey incorrect information. Therefore each location on continental earth (i.e. grid cell) would require a unique regression equation relating the changes in agricultural land use for that area in the past. This method can account for recent changes in the fertility of agricultural land and technology. The basic principle is to read in values from a gridded input from a number of years and use the relationship between the population of the world at that year to calculate regression coefficients for that grid cell. Then the model can calculate the extent of agriculture at a given point in time by inserting the population at that year into the regression equation.

2.2. Modeling algorithm

The HYDE 3.1 dataset (Goldewijk et al., 2010) of gridded cropland and grazing land from the years 1960, 1970, 1980, 1990, 2000, and 2005 were chosen to serve as the dependent variables when calculating the regression equations while the total global population served as the independent variables (Fig. 1). The input files are scale independent as the GLUDM model can adjust the internal variables according to the desired output scale. In this paper we use 5 arc-minute spatial resolution to readily align our results to the HYDE 3.1 maps. For each grid cell GLUDM reads in the values from

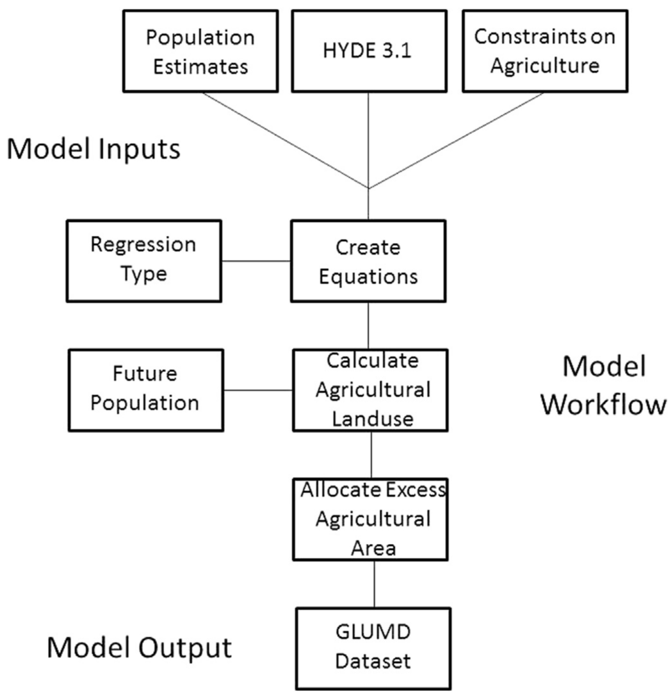

Fig. 1. The GLUDM model workflow. The model input includes a gridded layers of past landuse (e.g. cropland area), a table of global population in years corresponding to the landuse layers, and a gridded layer of spatial constraints on agriculture (e.g. latitude and altitude). Based on a user-defined equation type (e.g. linear, power-law), a unique regression equation is calculated for each grid cell (e.g. Fig. 2). The percent of landuse area in used-defined future year(s) within each grid cell is calculated using the unique regression equation. In case the calculated area exceeds 95%, excess landuse is allocated to neighboring cells. Finally a gridded output dataset is saved.

each of the input files as well as the population from each of those years to calculate the coefficients for the regression equation selected by the user (see for example Fig. 2 for a random grid cell). The calculated coefficients are combined with the equation to create a unique regression equation. While we use the HYDE dataset to generate the regression equations, this model is not limited to working with this dataset. It can be used with any gridded agricultural land use dataset as the regression equations are calculated each time the model is run. The HYDE dataset was chosen as it is the most complete land use dataset currently available. By default GLUDM comes with linear, exponential, and logarithmic functions but any type of regression equation can be added. In this paper we used linear regression for simplicity and as we have found this equation more closely matched the results of the HYDE dataset in most regions. The year chosen by the user is inserted into the equation to predict the total amount of agricultural land in that specific grid cell for the year in question. The output generated by GLUDM can be total cropland, total grazing land, total agricultural land use (combination of the cropland and grazing land) or all options. In addition to the gridded output, the values in each of the cells are totaled to calculate the global amount of the type of agricultural land selected.

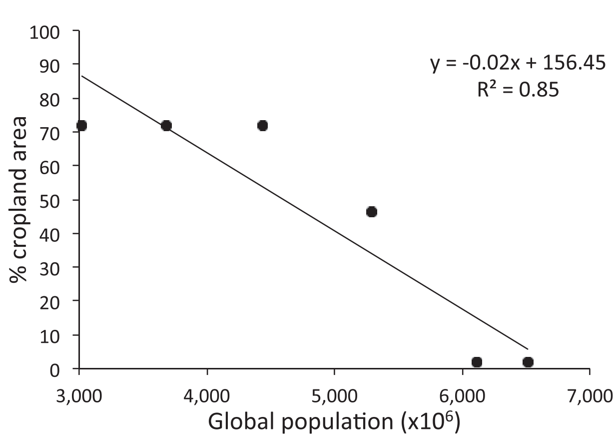

Fig. 2. Example of regression equation calculated for a single grid cell located at −86°, 33°. For this random grid cell cropland area is decreasing with increasing global population. Here we use a linear regression for simplicity but other regression types may yield more accurate predictions (will be the focus of future work). The regression equation is used to forecast cropland area in each grid-cell for a specific future year based on predicted global population for that year.

Several constraints are placed on the allocation of agricultural land. The first is that no agricultural land can exist above 66.5° north or south, the Arctic and Antarctic circles respectively. Additionally no cropland can exist above 4000 m above sea level and no grazing land can exist above 5500 m. Lastly, no agricultural land can exist in major built up urban areas. Slope was considered as a potential constraint but was excluded as the average slope across large grid cells is usually quite low and is irrelevant in areas where terraced fields are common. Climate change is not directly accounted for in the model. While climate projections are globally available, climate has a complex relationship with agricultural area which is not likely readily extractable from past trends. Another constraint is that no grid cell can have a percentage of agricultural greater than 95 percent. This was chosen because (in theory) no grid cell of significant size can be wholly converted to agriculture. A final obvious constraint is that no grid cell can have a percentage of agricultural land less than zero. These constraints can generate problems when allocating the amount of predicted cropland to the map. For example regression equations do not automatically "cap" at 95 percent. Although a check could be placed to cut values off at 95 and ignore the excess but this would violate the assumed relationship between total agricultural land and global population. To solve this problem excess agricultural land is redistributed among adjacent cells that have not reached their land use limit. A similar process is undertaken for cells that violate the latitude, altitude, and urban areas constraints. For the cells that have negative values generated by the regression equations (abandonment of agricultural lands) the deficit of agricultural land is distributed and removed from adjacent cells.

3. Results

3.1. Validation

An extensive validation of our model is not feasible given that there are very few estimates of total agricultural land use and virtually no estimates the future spatial distribution of agricultural. We therefore use 'hindcasting' in which we compare GLUDM results against established historical data. First the global amount of agricultural land predicted by GLUDM is compared to the known amount of agricultural land using the HYDE 3.1 and FAO Crop datasets (Goldewijk et al., 2010; FAO, 2013). Total changes in agricultural land are shown in Table 1. A Mann Whitney U Test showed the values of these three datasets (Table 1) are not significantly different ($p < 0.01$). The percent difference between GLUDM predictions and HYDE 3.1 and FAO Crop values is low with a maximum difference of 2.6% (against the FAO Crop for the year 2010) and average differences of 0.6 and 1.3% against the HYDE 3.1 and FAO Crop values respectively (Table 1). Fig. 3 plot temporal changes in global cropland area for the GLUDM, HYDE 3.1 and FAO Crop datasets. It shows that while GLUDM effectively predicts the long-

Table 1
The global amount of cropland (10^6 km^2) predicted by GLUDM compared to the HYDE 3.1 and FAO Foodstat datasets (Goldewijk et al. 2010; FAO, 2013). The percent difference between GLUDM predictions and the HYDE 3.1 and FAO Foodstat values are reported in the brackets.

Year	GLUDM crop	HYDE 3.1 crop	FAO crop
1960	1379	1368 (0.8%)	1370 (0.6%)
1970	1413	1421 (−0.5%)	1424 (−0.7%)
1980	1454	1451 (0.2%)	1453 (0.06%)
1990	1498	1520 (−1.4%)	1521 (−1.5%)
2000	1541	1530 (0.7%)	1514 (1.76%)
2005	1562	1557 (0.3%)	1536 (1.6%)
2010	1582		1541 (2.6%)
2020	1623		
2030	1656		
2040	1682		
2050	1700		
2060	1708		
2070	1709		
2080	1702		
2090	1688		
2010	1669		

term rate of change in cropland it does not capture yearly variability, which is likely controlled by economic or social drivers not explicitly incorporated into the model.

A visual comparison between GLUDM and HYDE 3.1 cropland maps show very strong correspondence for the years 1960 and 2005 (Fig. 4). For example, GLUDM predicted the massive expansion and migration of cropland form the east cost of the U.S. to the mid-west and southern Canada (Fig. 4). To evaluate the spatial distribution of potential biases, the values of each cell in the GLUDM predicted map were subtracted from the values in the HYDE 3.1 dataset for the same year. The absolute value of this difference was taken to display changes between the two datasets (Fig. 5). Southeast Asia and the Indian subcontinent show the greatest biases but overall large differences between GLUDM and the HYDE 3.1 values tend to be local. The largest percent difference was 47 (excluding the large urban areas where no agricultural land was allowed to be allocated) with an average difference of less than 3%. This strong correspondence is to be expected as the regression equations in GLUDM were developed using the HYDE 3.1 dataset making them collinear. This comparison is, nonetheless, valuable as it shows that the algorithmic solution employed in GLUDM (which differs from HYDE 3.1) is robust, yielding compatible predictions.

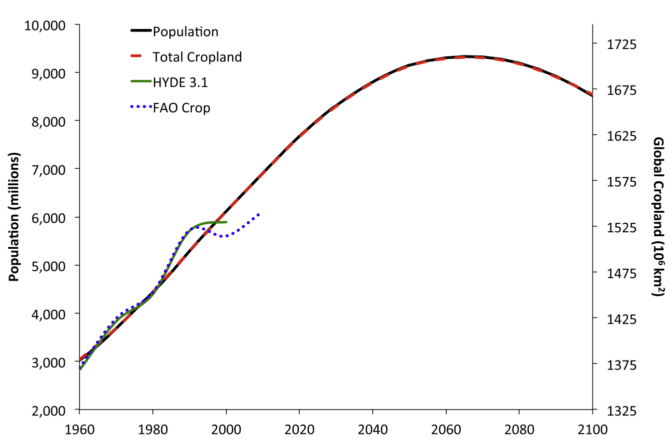

Fig. 3. Global population and cropland area between 1960 and 2100. GLUDM predicted cropland ('Total Cropland') match population changes and corresponds well to "observed" cropland changes from the HYDE 3.1 and FAO Crop datasets (Goldewijk et al. 2010; FAO, 2013).

The Ramankutty and Foley (1999) dataset was developed before and independently of the HYDE 3.1 dataset allowing for a direct comparison of results while controlling for colinearity. The statistical techniques used by Ramankutty and Foley (1999) create a superficial difference between the datasets. It is difficult to compare these datasets directly as they uses different land use area scales. Additionally the two datasets have a slightly different spatial extent prohibiting cell-to-cell comparison. Fig. 6 shows that, for c.e. 2000, the areas of high intensity of agriculture compare favorably to the output created by GLUDM. The Ramankutty and Foley (1999) dataset has a mean cell value of 10.53 and a standard deviation of 21.25 while GLUDM dataset has a mean cell value of 8.23 and a standard deviation of 16.54. This indicates the Ramankutty and Foley (1999) dataset displays both higher and lower concentrations of cropland than the GLUDM dataset.

As an additional validation metric the model output was compared against the USDA's CropScape dataset (Han, Yang, Di, & Mueller, 2012). This dataset represents the actual distribution of farmland cross the United States giving it an extremely high resolution and was selected to see how the distributions predicted by GLUDM compared to dataset derived from a different spatial scale. An area was selected at random which corresponded to a portion of the upper Midwest and was extracted from CropScape. Fig. 7 shows that as with the Ramankutty and Foley (1999) dataset, the CropScape data has a greater range of values. This may be attributable to scaling issues or the omission of a key, spatially heterogeneous, variable, showing that GLUDM tend to smooth out local spatial trends.

3.2. Future cropland predictions

Globally, considerable expansion in agricultural lands is shown at the end of the 20th century and the start of the 21st century (Fig. 3 and Table 1). GLUDM predicted that global cropland area between 2005 and 2050 would increase by 18%. This value corresponds very well to previous predictions by other models (Schmitz et al., 2014 cited a range of 10–25% predicted by 7 out of 10 models they reviewed). This increase in cropland area is most pronounced over central US, Europe, central Africa, southeastern South America and eastern Asia (Fig. 8). Relatively small changes in cropland are predicted after the 2020s. This is because population growth rate is predicted to decrease after 2020, turning negative after 2060 (Fig. 3).

The following description of future cropland trends is based on average cropland area and percent change since the year 2000 (Fig. 9) in 14 regions (Fig. 10) and maps of decadal percent change in cropland area (Fig. 11):

North and Central America – considerable increases in cropland area are predicted for central North America and Central America during the 2020s. These coincide with decreases in eastern U.S. This is a continuation of an historical trend since the middle of the 20th century (Fig. 4) and GLUDM predicted it would continue, but at a slower rate, until the 2050s. In the last two decades of the 21st century this trend will inverse leading to widespread decline in cropland area in central North and Central America.

South America – cropland area is predicted to increase in northern and southeastern South America up to the 2050s. The rate of this trend decreases during the first half of the 21st century.

Europe – highly heterogeneous trends are predicted throughout Europe for the first half of the 21st century. The overall trend is a decreasing cropland area during the first half of the century followed by very little change in the second half.

Middle East and North Africa – The northern extents of the Middle East (Turkey and Iraq) show fairly heterogeneous trends with a general increase in cropland area at the first half of the century followed by a decreasing trend at the end of the century (2080s and 2090s). The most intense trends are along the Tigris-

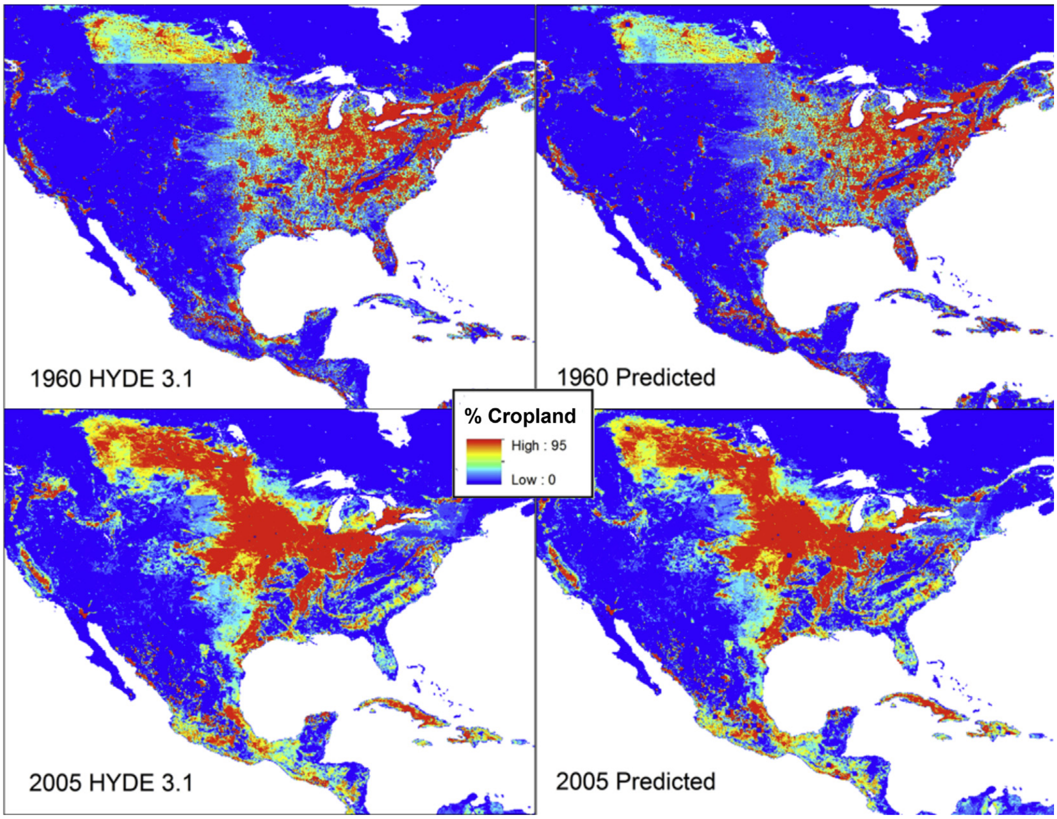

Fig. 4. The GLUDM dataset is compared against the HYDE 3.1 dataset (Goldewijk et al. 2010) for the years 1960 and 2005 over North America. The squares with low values in the GLUDM results are urban areas (Hyde 3.1 does not explicitly account for urban areas).

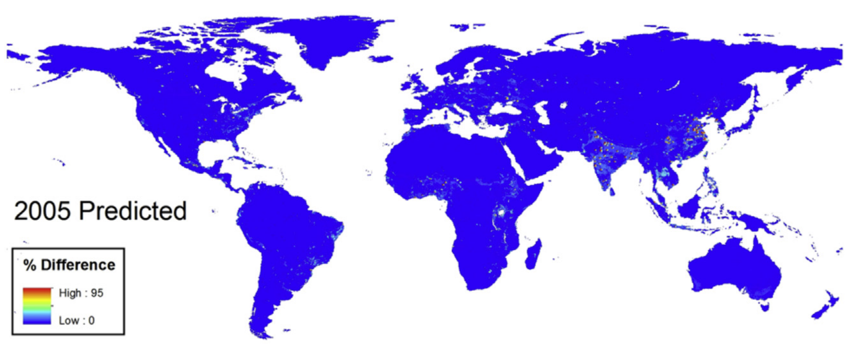

Fig. 5. The difference in each cell value between the Hyde 3.1 dataset (Goldewijk et al. 2010) and GLUDM predicted cropland for the year 2005.

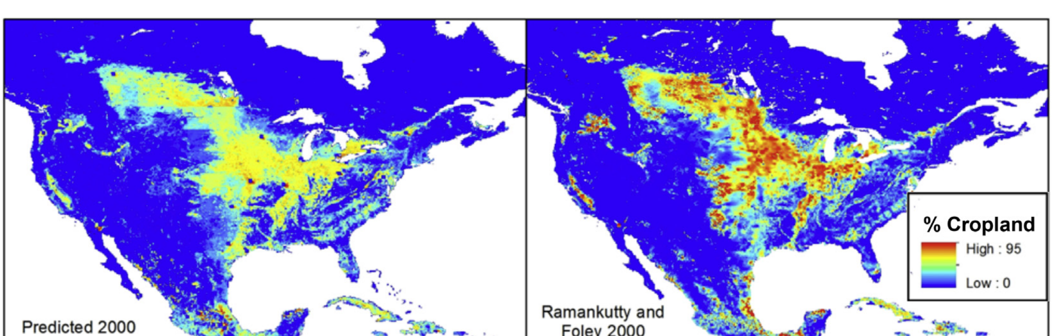

Fig. 6. The GLUDM cropland predictions are compared to the Ramankutty and Foley (1999) dataset for the year 2000.

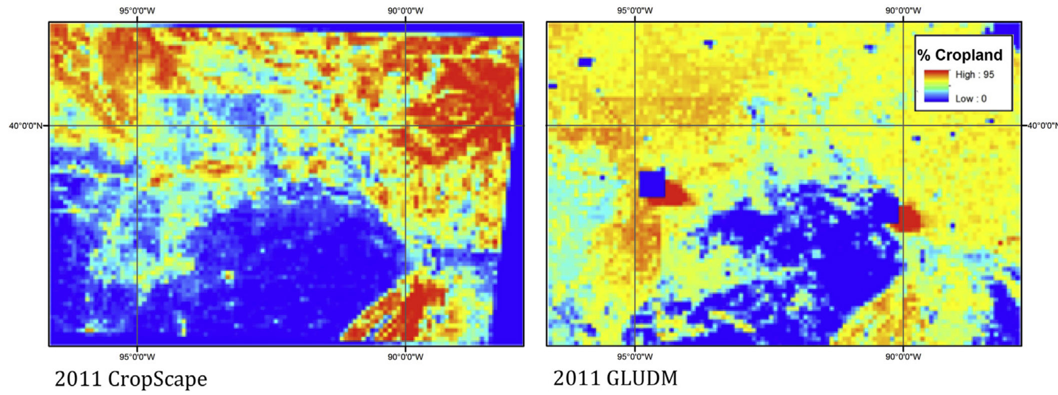

Fig. 7. The GLUDM cropland predictions are compared to the CropScape (Han et al., 2012) dataset for the year 2011. This area is located in the Upper Mississippi Valley.

Euphrates basin in Iraq and northwestern Iran. Most of the Middle East and North Africa show relatively little change in cropland during the 21st century.

Tropical Africa – extensive and intense increases in cropland is predicted for central and southern Africa during the 2020s and 30s. This trend weakens in the 2040s and is reversed in the last two decades of the 21st century. The most substantial changes are predicted for regions north of the equator and the eastern part of southern Africa.

Former USSR – similar trend as predicted for Europe. Overall, relatively small changes in cropland area during the 21st century.

Indian subcontinent (South Asia) – highly heterogeneous

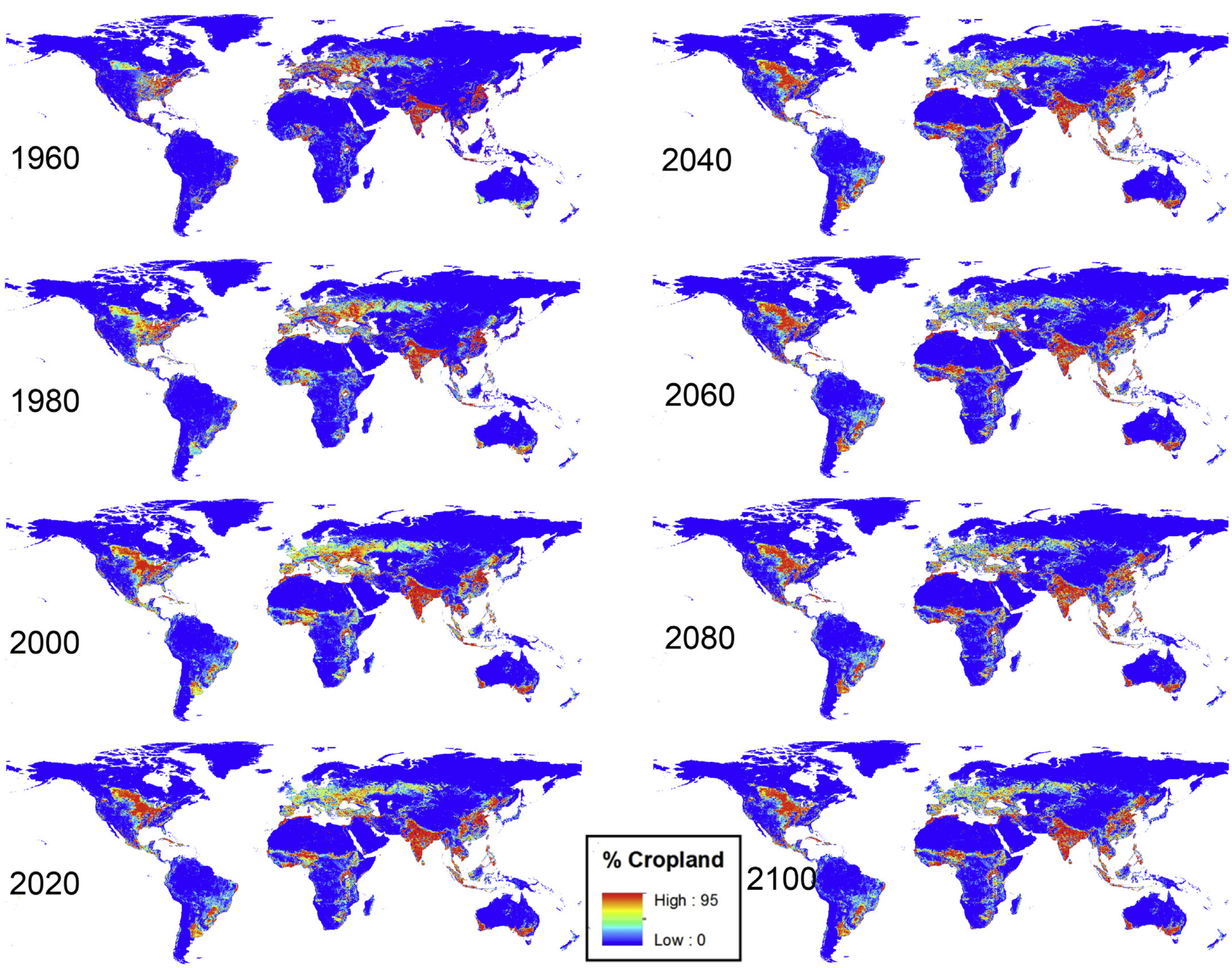

Fig. 8. GLUDM predicted cropland for the years 1960, 1980, 2000, 2020, 2040, 2060, 2080 and 2100.

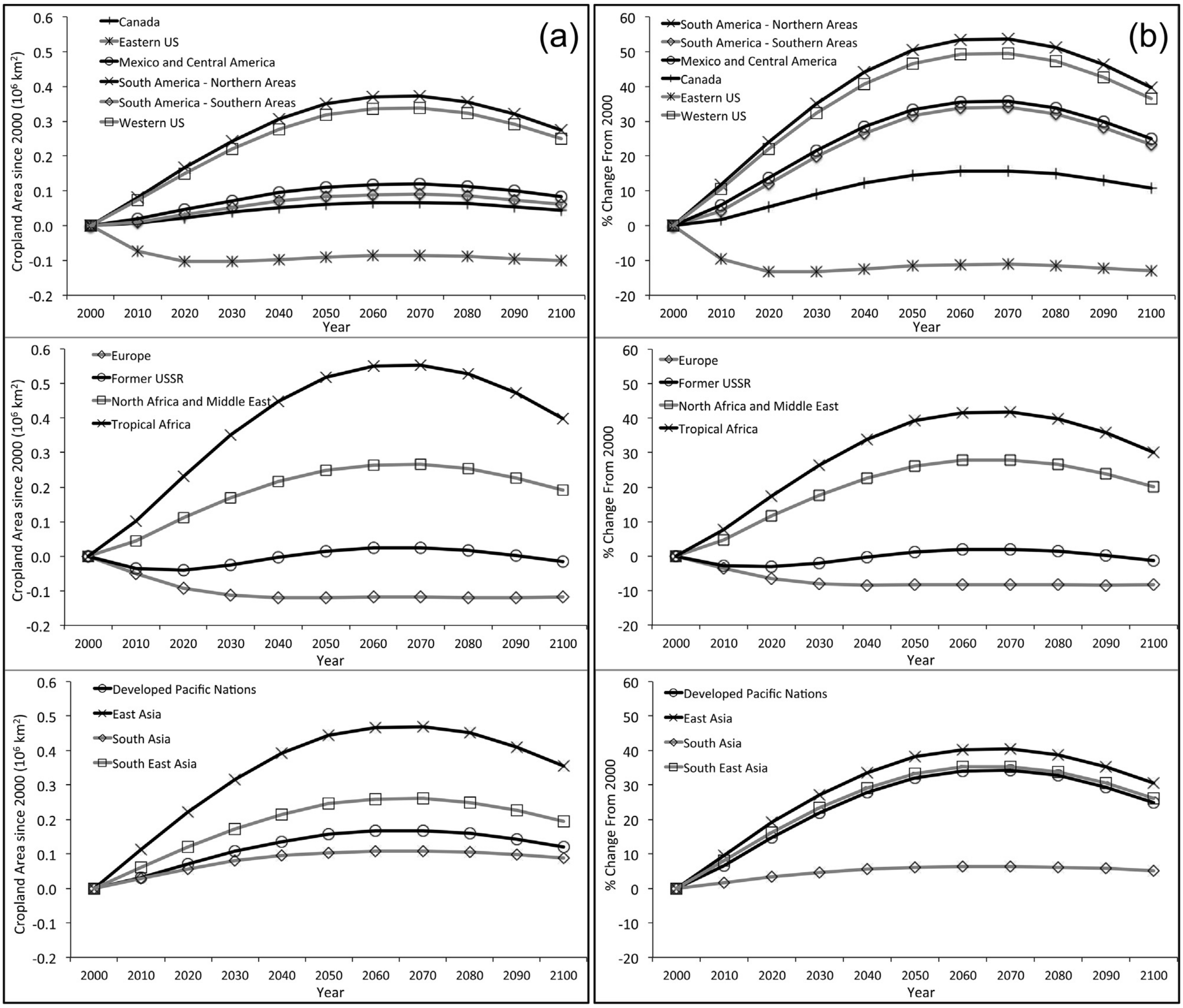

Fig. 9. (a) Changes in cropland area since 2000 and (b) percent change in cropland area since 2000 in 14 world regions (Fig. 9).

trends throughout the 21st century. For the 2020s–2040s, considerable decreases in cropland area were predicted in central India; coinciding with intense increases in northern and southern India. These trends are reversed in the last two decades of the 21st century.

East Asia – fairly heterogeneous trends with extensive and intensive increases in cropland area in most in the southeast and central China during the 2020s–2040s; coinciding with intensive decreases in eastern China and Myanmar. These trends are reversed in the last two decades of the 21st century. Overall the changes in cropland are a considerable increase up to the 2050s followed by less intense decrease.

Australia – fairly intensive increases in cropland areas were predicted in southeast southwest Australia during the 2020s and 2030s. These trends are reversed in the last two decades of the 21st century.

3.3. Spatial trends in regression coefficients and correlation

The spatial distribution of the regression equation slope in each grid-cell (Fig. 12) provides a more direct mapping of the trend in cropland area between 1960 and 2005 (the years used to calculate the equations). The migration of cropland from the east coast of North America to its central part is clearly visible (positive and negative slopes respectfully). A result of this migration is the U.S. Canadian border can be clearly observed as Canadian cropland expansion in the Northern Great Plains has slowed over the last half century while it has greatly increased in the U.S. The migration of cropland from increasing population regions is also visible in Australia in which the east cost (with the highest population density) shows a strong negative trend while west and south regions of the country show increasing trends.

The aforementioned heterogeneity in future cropland dynamics in Europe and Eastern Asia is clearly explained by the distribution of past trends (regression equation slope) in these regions (Fig. 12). Overall, an emerging trend in cropland dynamics is the migration of food production from many developed countries to developing countries (from Europe and East Asia to Africa, South America and South East Asia).

The distribution of the regression equations' R^2 (Fig. 13) is indicative of the correlation between global population trends and cropland dynamics in each grid-cell. The black color is for grid-cells with zero cropland. These are mostly high altitude and latitude and arid regions. These 'zero cropland' regions also occupy a large

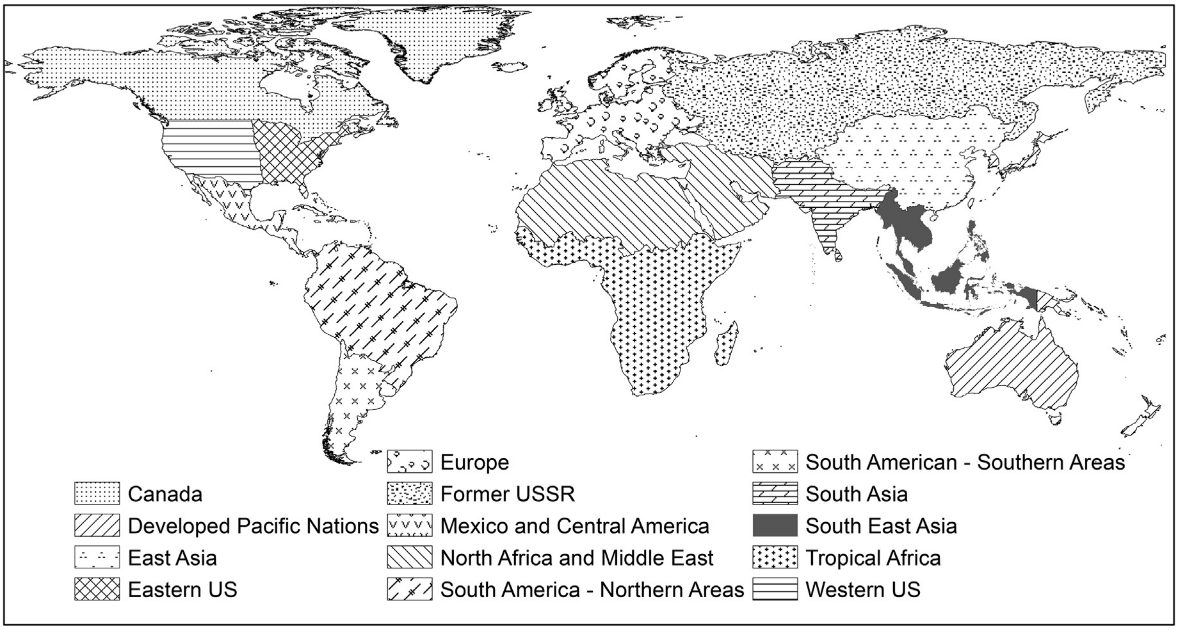

Fig. 10. World regions used for calculating temporal changes in cropland (Fig. 8). These regions were modified from Ramankutty and Foley (1999).

proportion of the Amazon Basin. This is because these regions are completely forested. The central part of the Amazon Basin shows a particularly low R^2 values. North America, Australia and Central Asia and most of South America (except the Amazon Basin) show strong correlations. Europe and Africa shows a more heterogeneous distribution of the R^2. More work is needed to elucidate the drivers and processes leading to these results but overall they suggest that the effect of global dynamics has a varying degree of influence on regional agricultural dynamics.

Comparing Figs. 12 and 13 shows that the regression equation slope is not a significant driver of the correlation R^2 (the correlation coefficient between the two maps is 0.12). This suggests that the model accuracy is not biased by the rate or direction (increasing or decreasing) of cropland change.

4. Discussion

Using regression equations to make predictions far into the future is always problematic, especially when dealing with phenomenon controlled by many variables, as significant abstraction is necessary to simplify the calculations. A basic assumption made by GLUDM is that agricultural technology will continue to increase at a similar rate as it has in the past. Most experts agree that the techniques used introduced during the Green Revolution have reached their maximum effectiveness (Hurtt, Chini, Frolking, Betts, & Feddema, 2011). Despite this there is reason to believe that a combination of planting more calorie rich foods, maximization of cropland, and better harvesting and shipping methods could sustain the current level of increased production (Foley et al., 2005).

Another significant assumption in our model is that future climate change will not significantly effect the production and distribution of agricultural land (DeFries, Bounoua, & Collatz, 2002). Excluding this variable may not significantly impact the total amount of agricultural land needed. While climate change will undoubtedly decrease production in the mid-latitudes it may greatly increase production in the upper latitudes. Unfortunately these changes will not be captured in the spatial distribution provided by the current version of the model, unless there is a strong preexisting relationship that is projected into the future. An example of this problem is the 45% increase in cropland area above year 2000 levels in the Western United States. While agriculture expanded rapidly in the region during the 20th century the current climate trends of higher temperatures, more frequent drought, and dwindling groundwater resources may not allow further expansion.

There are several noteworthy uncertainties with GLUDM predictions. The first is the global population predictions (the HYDE 3.1 dataset in this paper). Bias in this independent parameter will directly affect the accuracy of the results. A second issue relates to the fact that the model does not explicitly account for agricultural intensity. The total amount of agricultural land under production in a given area does not necessarily equate to the intensity of agriculture at that location. Thus the output from this model alone may not be suitable for certain applications (e.g. estimating caloric yield).

The GLUDM modeling approach may not be very robust for time periods that come after a decrease in population as the model is based upon regression equations. For example the global population in 2050 and 2084 are estimated to be essentially equal at 9.1 billion. Thus the model will display the exact same outputs for each of these years. As GLUDM is not an iterative model it does not have the ability to differentiate between earlier and later points in time. Thus the shift from agricultural production in central North America back towards Eastern North America is almost certainly inaccurate. Because of this deficiency GLUDM seems best suited for predicting changes in agricultural land use over short intervals into the future (20–50 years).

GLUDM will serve as a steppingstone toward the development of a more comprehensive model for predicting the spatial extent of global agricultural production. The DynaCLUE model has already shown that through the quantification of environmental and technological variables it is possible to estimate the potential agricultural production of an area (Trisurat, Alkemade, & Verburg, 2010). It is also possible to quantify the global requirements of food and economical drivers. Thus the combination of an agricultural production model with GLUDM, for example, would allow for

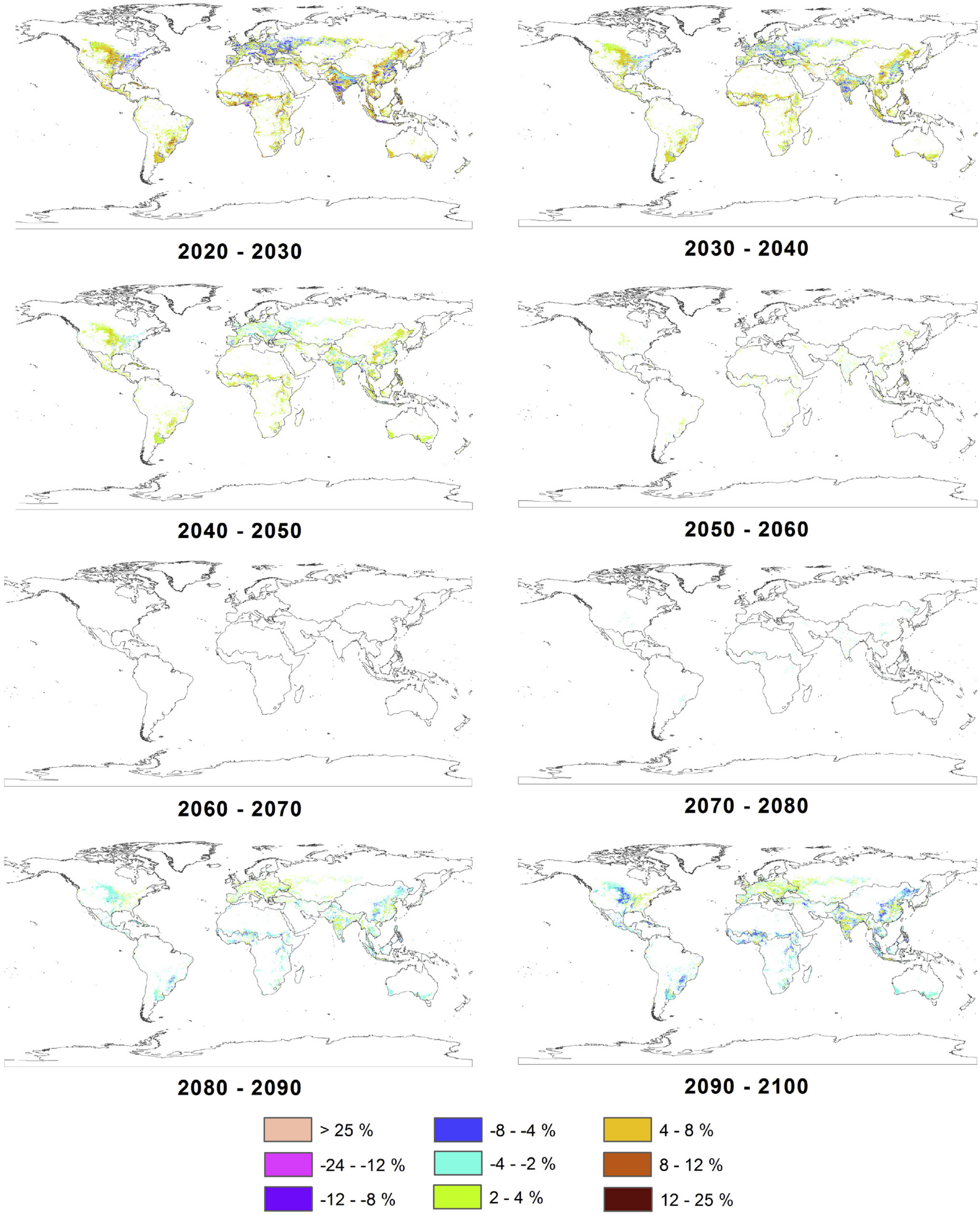

Fig. 11. Predicted percent change in global cropland distribution over 10 year intervals from 2020 to 2100. Note that white indicates zero percent change.

land to be allocated for agricultural production until the potential production matched the requirements of the global population. This kind of model development could provide a framework for investigating agricultural land use scenarios by allowing users to control all of the variables used in each simulation.

Despite of these limitations and uncertainties, GLUDM offer a robust first-order estimate of global agricultural land use dynamics into the future. This is a highly novel product that can benefit a multitude of earth surface and atmospheric modeling framework and provide a platform for studying the spatial and temporal

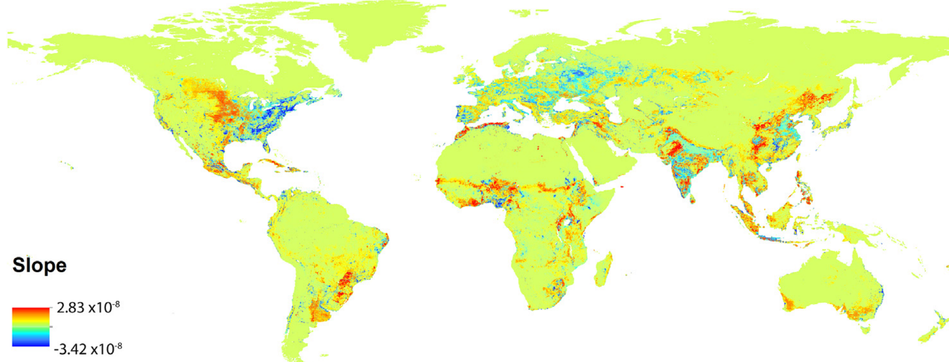

Fig. 12. Regression equation slope as derived from the relationship between cropland area in each grid-cell and global population change between 1960 and 2005.

dynamics in anthropogenic impact on terrestrial land cover.

The modeling results show some intriguing trends in the future of the world's biological systems in the next 50 years. East Asia is predicted to continue on its current trajectory of expanding agricultural land use, loss of environmental services, and dwindling water resources with a 40% increase in cropland area above year 2000 levels. Adjacent South Asia however will experience only a slight increase despite its growing population. In this region of cyclic droughts it is possible the farmers of South Asia have already tapped all available land suitable for agriculture. Tropical Africa will see a 40% increase in cropland area to feed its surging population. This growth will further degrade Sahel and tropical forest ecosystems and may increase the probability of war over resources in this volatile region (NRC, 2013). Similarly, cropland in Northern South America is predicted to increase over 50 percent above year 2000 levels with some of the world's most pristine forests being lost to agricultural expansion.

The model results also show some positive signs. Agricultural land use in the Eastern United States is expected to decrease by 10% freeing up land for reforestation, greenways, and nature preserves. The amount of agricultural land in Europe is also expected to decrease by 10%. Will this allow for an expansion of Europe's nation park system and an expansion of the ranges of the European Bison, European Wolf, and Eurasian Brown Bear? Agricultural production in the Former USSR is also predicted to decrease slightly. How will this affect Russia's exports of agricultural products?

5. Conclusion

GLUDM is a gridded, statistical model that uses recent trends in the relationship between global population and agricultural land use to calculate regression equation coefficients to estimate the global distribution of cropland a number of years in the future. A key strength of this model is that it creates unique regression coefficients for each grid cell allowing the model to generate a spatially explicit output. It offers a much simpler numerical platform for predicting and analyzing future land use trends compared to more sophisticated land use models. Moreover, GLUDM is easy to use, easy to customize, and the input data is readily available. Weaknesses relate to the facts that the regression equations cannot yet explicitly capture changes in the rate of agricultural productivity and account for crucial factors in global agricultural product such as economic, legal, climatological, and technological variables. Future work on this model will focus on incorporating the variables listed above.

While it is difficult to validate models which predict future changes our model results seem reasonable given “hindcast” comparisons to other datasets. This was true through comparisons to large scale datasets such as the HYDE 3.1 and the Ramankutty and Foley (1999) dataset as well as to small scale datasets such as the USDA's CropScape. Globally, 18% increase in cropland area is predicted between 2005 and 2050 which corresponds very well to previous estimations. Following 2050, a general decrease in

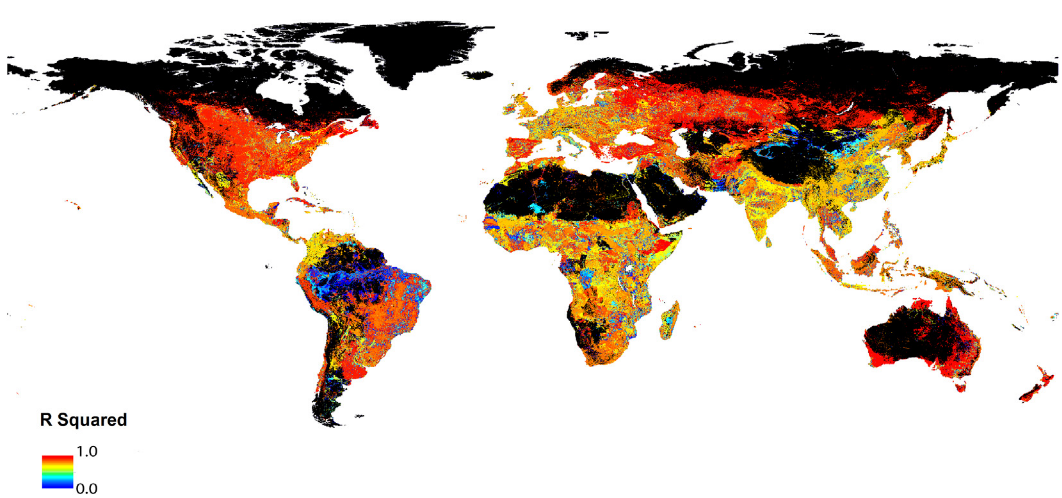

Fig. 13. Regression coefficient of determination (R^2) as derived from the relationship between cropland area in each grid-cell and global population change between 1960 and 2005.

cropland area is predicted. GLUDM predicts surges in agricultural land use in Northern South America, East Asia, and Tropical Africa while predicting decreases in agricultural production in Europe and Eastern North America. These predictions carry a number of implications for future biodiversity, environmental degradation and economic development in these areas.

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