

# The effect of climate change on rural land cover patterns in the Central United States

Christopher Lant<sup>1</sup> • Timothy J. Stoebner<sup>2</sup> • Justin T. Schoof<sup>3</sup> • Benjamin Crabb<sup>4</sup>

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Abstract This study projects land cover probabilities under climate change for corn (maize), soybeans, spring and winter wheat, winter wheat-soybean double cropping, cotton, grassland and forest across 16 central U.S. states at a high spatial resolution (see https://doi.pangaea.de/10.1594/ PANGAEA.859593?format=html), while also taking into account the influence of soil characteristics and topography. The scenarios span three coupled climate models, three Representative Concentration Pathways (RCPs), and three time periods (2040, 2070, 2100). As climate change intensifies, the suitable area for all six crops display large northward shifts. Total suitable area for winter wheat and for winter wheat-soybean double-cropping expand northward, while cotton suitability migrates to new, more northerly, locations. Grassland intensifies in the western Great Plains as crop suitability diminishes; suitability for forest intensifies in the south while yielding to crops in the north. To maintain current broad geographic patterns of land use, large changes in the thermal response of crops such as corn would be required. A transition from corn-soybean rotations to winter wheat-soybean doubling cropping is an alternative adaptation.

**Keywords** Climate change adaptation · Climatic downscaling · Land use land cover change · U.S. Midwest

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Christopher Lant chris.lant@usu.edu

- <sup>1</sup> Department of Environment and Society and Utah Agricultural Experiment Station, Utah State University, Logan, UT, USA
- <sup>2</sup> Environmental Systems Research Institute, San Antonio, TX, USA
- <sup>3</sup> Department of Geography and Environment Resources, Southern Illinois University, Carbondale, IL, USA
- <sup>4</sup> Remote Sensing/GIS Lab, Quinney College of Natural Resources, Utah State University, Logan, UT, USA

## 1 Study purpose

The United States is the world's leading producer of corn (maize), second in soybeans, and fourth in wheat; the central U.S. is the leading exporting region for all three staple crops (U.S. Department of Agriculture, Foreign Agricultural Service 2015). Adaptation to future climatic changes will substantially alter the geographic pattern of these rural land uses with implications for agricultural productivity, the region's landscape patterns, and thus its biodiversity (Radeloff et al. 2012), capacity to provide ecosystem services (Power 2010; Tilman et al. 2002), and biogeochemical cycling (Vitousek et al. 1997). Climate change-induced land use changes also feedback to climate through changes in albedo and evapotranspiration, as well as terrestrial carbon storage (Bonan 2008; Stohlgren et al. 1998).

This paper examines quantitatively the potential geographic response of eight predominant central U.S. rural land covers (corn, soybeans, spring and winter wheat, winter wheat-soybean double-cropping, cotton, grassland, and forest) to climate change scenarios in 2040, 2070, and 2100 using three contemporary climate models (atmosphere-ocean general circulation models (AOGCMs) or earth systems models (ESMs)) and three Representative Concentration Pathways (RCPs). We place special emphasis on corn, which economically dominates other central U.S. land covers with which it is either competitive (e.g., wheat, grassland, forest), or complementary (e.g., soybeans) (McPhail and Babcock 2008; Searchinger et al. 2008; Mehaffey et al. 2011) and on winter wheat-soybean double cropping, which Siefert and Lobell (2015) identify as an important potential adaptation to climate change.

#### 1.1 Land change modeling approach

The National Research Council (2014) outlines approaches to the rapidly growing field of land change modeling along a continuum from statistical and machine-learning approaches, which rely heavily upon empirical calibration and assume stationarity in processes of landscape change, to cellular, spatial econometric, and agent-based approaches, which, in an increasingly complex manner, incorporate spatial contagion, economic response, and interactive decision-making processes that drive land use change. They point out the need for more accurate projections of land use change at higher spatial resolution, while acknowledging that prediction of future landscape patterns is fraught with uncertainties that derive not only from the stochastic nature of land change processes and their embeddedness in evolving social structures, but from path dependency (Verburg et al. 2004), especially when spatial contagion effects are strong.

The modeling strategy presented here adapts biogeographical methods of projecting changes in the spatial pattern of habitat for individual species in response to climate change (see Austin 2007; Franklin 2010; Guisan et al. 2002; Pearson et al. 2006) to the case of a humandominated agricultural landscape. While dispersal mechanisms make predicting occupation of emerging wildlife habitats difficult (Araujo and Peterson 2012; Elith et al. 2010), modern communication and transport technologies make the assumption of rapid dispersal valid for crops. Previous research shows that spatial contagion processes in the rural U.S. Midwest landscape are especially weak (Stoebner and Lant 2014), even if prior use of the parcel, through crop rotation and the relative permanence of forests, does have an important influence. In the rural (as opposed to urban) central U.S., this weakness of spatial contagion effects, and short-lived temporal dependency reduces the uncertainties generated by path dependency, making long-term projections more viable.

The application of a species habitat modeling approach to a human-dominated landscape, however, assumes that social processes that have generated the current landscape will remain stationary through the projection period. Under prices, policies, technology regimes, and agribusiness structures that have obtained over the last several decades, on low-slope rural land with favorable edaphic and climatic characteristics, corn-soybean rotations have driven wheat to fertile lands with drier and colder (spring wheat) or warmer (winter wheat) climates, grassland to drier climates, steeper topographies and less fertile soils, and relegated forests to remnant wetlands and, where climates are humid, steep lands with infertile (often acidic) soils. Correlations between the geographical occurrences of these land covers and the climatic and edaphic factors that define their current 'habitat' therefore reflect a zone of suitability that is in fact partly socio-economic. The statistical, empirical approach to land use modeling we here adopt thus assumes stationarity across the twenty-first century projection period in the underlying socioeconomic and agronomic causal pathways that have generated correlations between extant land uses and their climatic and edaphic determinants. This issue underlies projections in general – with their if (these conditions obtain) – then (this is the most likely outcome) logical structure, and distinguishes them from predictions.

This approach does present limitations. Over the course of the projection period, these agroeconomic relationships could, and probably will, change due to shifts in crop genetics, agricultural production technologies, demography, consumer preferences, relative prices, agricultural and environmental policies, the interaction among these, and other factors that may subsequently emerge. Given this vast unpredictability of social driving factors that influence land use change, as compared to a more definable envelop of possible climatic futures, we have focused here on the latter.

## 1.2 The central U.S. landscape: previous research

This study complements previous investigations of future agricultural productivity and landscape patterns in the central U.S. Recent studies of land change in the U.S. have varied in their use of land use data sets and methodological strategies. Sleeter et al. (2013) and Sohl et al. (2014) use the National Land Cover Database and Landsat imagery at five time intervals to assess land cover change in ecoregions of the conterminous U.S. from 1972 to 2000 at a spatial resolution of 10 km and to map forest stand age through 2100 for the conterminous U.S. at 250 m resolution. Using National Resource Inventory data, Radeloff et al. (2012) project four categories of land use (urban, forest, cropland, rangeland) for 2051 at a 100 m scale for the conterminous U.S. under four scenarios, none of them climate-related. With a focus on landscape carbon dynamics, Strengers et al. (2004) utilize IPCC scenarios within the Integrated Model to Assess the Global Environment (IMAGE 2.2) model among 17 world regions at a 0.5° scale. Using the FORE-SCE model, Sleeter et al. (2012) utilize IPCC-SRES scenarios to generate demand for conversions to commodity-producing landscapes and then project these among U.S. ecoregions; Sohl et al. (2012) project 16 land cover classifications (aggregating cultivated crops into one class) through 2100 for the Great Plains under IPCC-SRES scenarios. FORE-SCE employs data layers of topographic, edaphic, climatic and spatial information in a logistic regression approach to derive suitability-of-occurrence surfaces for each land cover class, a general strategy that we also here adopt, building upon and complementing these studies by (a) using a higher spatial resolution dataset from a different source (the USDA/NASS Cropland Data Layer), (b) employing greater crop specificity, (c) developing high spatial resolution climate scenarios based upon IPCCs Representative Concentration Pathways (RCPs), and (d) taking a non-linear approach – multivariate fractional polynomials (MFP) – to determining the effect of climatic, edaphic and topographic factors on land cover suitability.

## 2 Methods

## 2.1 Land use data and study area

The USDA/NASS Cropland Data Layer (CDL) (Han et al. 2012) forms the foundation for this study. According to USDA metadata (see Supplementary Table 1), the dataset correctly identifies 30 m pixels with 88 % accuracy from among land cover categories disaggregated into individual crops, with 94 % accuracy for corn and soybeans (NASS 2013). Accuracies for principal crops in each state are far higher, generally over 85 %, than for secondary crops, grassland and forest. We selected corn, soybeans, winter and spring wheat, winter wheat-soybean double cropping, cotton, grassland and forest, which collectively occupy 83 % of the central U.S. study area. As part of a larger study on "Climate, Hydrology and Landscapes of America's Heartland," each of the 16 states for which CDL data were available 2007–2011 defines the contiguous Central U.S. study area with a total of 3.2 billion pixel-years of categorical data. The area overlying the Ogallala aquifer was omitted to focus the analysis on rainfed rather than irrigated agriculture. The adoption or cessation of irrigation is potentially an important adaptation to climate change that involves trade-offs among irrigation investments and drought risk mitigation, availability of groundwater resources, and other factors that are beyond the scope of the present study (Koundouri et al. 2006).

## 2.2 Geographic determinants of land covers

Possible determinants of the eight land covers studied include climate, soil, and topographic variables; many forms of these were tested as potential explanatory variables. Soil (e.g., pH, available water capacity) and slope characteristics were obtained from the SSURGO database (Soil Survey Staff 2011). Climatic data, including air temperature and precipitation, were obtained from the Global Summary of the Day-National Climatic Data Center (NCDC 2012) for each of 214 weather stations in the 16-state study area. Because planting decisions are based on past climate, not future weather, each pixel-year was associated with rasterized historical climate data from 2001 to 2010 from the Integrated Surface Hourly dataset (available from NOAA/NCEI) and the Climate Prediction Center (CPC) 0.25° Daily US Unified Precipitation dataset (Higgins et al. 2000). Two synthetic climatic parameters predict specific land covers in pixels with a high degree of explanatory power: summer (June–August) growing degree-days (GDD) (a crop-specific measure of temperatures above a threshold and below a maximum, accumulated on a daily basis) (Womach 2005) and growing season (April–October) water surplus (precipitation minus potential evapotranspiration).

#### 2.3 Sampling process

After eliminating the Ogallala area and land covers not studied, a sample of roughly 200,000 pixels was selected from the years 2008–2011, with a 1000-m minimum distance to control for spatial autocorrelation. For each land cover, an equal number of occurrences and non-

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occurrences (1280 for cotton; 2560 for double-crop; 4000 for the other covers) were randomly selected to improve accuracy in logistic regression models (Franklin 2010; Miller 2010). Separate calibration and validation datasets were employed.

#### 2.4 Land cover suitability model construction

Non-linear approaches employed in species distribution modeling include multivariate adaptive regression splines (MARS), classification and regression tree (CART), generalized additive models (GAM), and multivariable fractional polynomials (MFP) (Guisan et al. 2002; Hastie and Tibshirani 1987; Hosmer and Lemeshow 2000). MARS and CART, however, do not provide regression coefficients that can be matched with independent variable values for specific pixels necessary for raster calculation techniques. The GAM technique is computationally intensive and therefore convergence cannot reliably be obtained with a large dataset. MFP provides regression coefficients that can be utilized in raster calculations and can process very large datasets; it was therefore employed in a logistic regression context.

MFP is a non-parametric fitting model originally developed for diagnoses in medical research (Sauerbrei and Royston 1999) that uses exponential powers to transform variables that produce a non-parametric fit, allowing the modeler to use continuous data even when the distribution is not normal or the variable relationship is not linear (Hosmer and Lemeshow 2000; Meier-Hirmer et al. 2003). To our knowledge, this study represents the first use of MFP in land cover or habitat modeling.

Following the revised advice of Pontius and Millones (2011) to avoid Kappa, we used percent correct, sensitivity, specificity, and relative operating characteristic (ROC) as measures of model fit. Also referred to as receiver operating characteristic (van Asselen and Verburg 2012) and calculated as area under the curve (AUC), the ROC curve is a plot of the true-positive rate versus the false-positive rate for every potential threshold within the model ranging from 0.5 (random) to 1.0 (perfect fit). Swets (1988) identifies ROC as a precise and valid measure free of decision biases and prior probabilities. Franklin (2010) and Miller (2010) cite an ROC score above 0.7 as a good model and above 0.9 as a very high quality model.

## 2.5 Climatic projections

Statistical downscaling techniques were used to develop high spatial resolution projections of the driving climatic variables on the basis of output from transient AOGCM/ESM simulations. For precipitation, a scaling technique described by (Wilks 1999) and modified as described in (Schoof 2015) was utilized. For temperature, multiple regression using large-scale circulation and thermodynamic descriptors was used to derive rasterized station-based projections, as in Schoof et al. (2007). The outputs of the downscaling exercise were parameters of a weather generator that was used to produce high-resolution daily time series; these were then used for computation of water surplus and growing degree-days (GDDs).

The Coupled Model Intercomparison Project (CMIP5) data portal includes output from a large number of AOGCMs and ESMs. Rather than consider the entire CMIP5 archive, we chose three models on the basis of Sheffield et al. (2013), who evaluated historical CMIP5 model performance for North America and Knutti et al. (2013), who demonstrated the substantive overlap between models that results from adoption of common model components (e.g., the same oceanic or atmospheric model). The chosen models therefore perform well for North America, but also span the 'genealogy' of contemporary climate models. As shown by

Maloney et al. (2013), these models provide a fair representation of the broader CMIP5 archive for North America over a range of temperature, precipitation, and circulation-related metrics. The models used in this analysis include (1) the L'Institut Pierre-Simon Laplace Coupled Model, Version 5 (IPSL-CM5-LR), (2) the Meteorological Research Institute Coupled Atmosphere–Ocean General Circulation Model, Version 3 (MRI-CGCM3), and (3) the Norwegian Earth System Model, Version 1 (NORESM-1 M). These models are hereafter referred to as IPSL, MRI, and NOR, respectively.

Climate scenarios were selected based on the concept of Representative Concentration Pathways (RCPs) that underlie the future climate projections developed as part of CMIP5. RCPs 2.6, 4.5, and 8.5 were selected to represent low, medium, and high trajectories of twenty-first Century greenhouse gas (GHG) emissions. Each combination of GCM and RCP was projected for 2040, 2070, and 2100, forming the basis for 27 geographical projections for each land cover. Among these, three scenarios, the MRI–RCP–2.6 for 2040, the IPSL–RCP–4.5 for 2070 and the NOR–RCP–8.5 for 2100 span the range of the scenario space employed, and are used for projecting geographic shifts in suitability for the eight land covers studied.

### **3 Results**

#### 3.1 Response models

Non-linear logistic regression models for each land cover performed at a high level with ROC scores ranging from 0.828–0.965 (Table 1) for all land covers except grassland (0.711), which has more generalized habitat requirements and is less accurately identified in the Cropland Data Layer (Supplementary Table 1). The proportion of correct predictions ranges from 0.655 for grassland to 0.914 for spring wheat (Table 1). Because of the complex non-linearities produced by the MFP technique, regression coefficients are non-intuitive, but the overall nonlinear effect of each land use determinant can be shown graphically (Fig. 1).

Corn and soybeans have a similar thermal peak at 1085 and 1106 GDDs, respectively, but soybeans exhibit a larger thermal range (where probability exceeds 0.1) from 832 to 1575 GDDs compared to only 873–1474 GDDs for corn. Cotton has a very narrow and warmer thermal range (1328–1527 GDDs), with a warmer peak than for winter wheat-soybeans double cropping, whose thermal range is broader (1130–1672 GDDs). Spring wheat peaks at cooler (914 GDDs) and winter wheat peaks at warmer (1900 GDDs) climates. The thermal response of forest, and to a lesser extent grassland, reflect their economically subordinate status to the crops studied. Note that the study area does not capture the complete latitudinal range of either form of wheat, grassland, or forest.

The response to water surplus shows a similar optimum for corn (323 mm) and soybeans (281 mm) and similar range (corn -61-616 mm, soybeans -1-700 mm). Both forms of wheat peak near the humid-arid threshold of 0 mm, while suitability for forest increases with water surplus. Grassland suitability reflects its subordinate status, while also dominating non-irrigated areas with larger water deficits up to 400 mm.

Edaphically, forest dominates on acidic soils, while corn and soybeans occupy the more fertile soils with higher available water capacity. All crops show exponentially decreasing suitability as slopes increase, while the probability of forest increases with slope. Grassland peaks at intermediate slopes of 10–20 %. These responses are consistent with agronomic research (Huang and Khanna 2012; Sun and Van Kooten 2013).

MHP Iransionation         Corn         Sybran         Winter wheat         Spring wheat         Cotion         Double copy $-3$ $-42.159$ $-98.300$ $4.2869$ $-29.434$ $-157.15$ $-19.005$ $3$ $-3$ $-42.159$ $-98.300$ $4.2869$ $-157.15$ $-19.005$ $2$ $-2$ $-19.925$ $-150.66$ $-150.66$ $-150.66$ $2$ $-0.5$ $-172.06$ $107.93$ $-172.06$ $9.3554$ $2$ $-1160$ $81.575$ $-2.8508$ $-13.957$ $-172.06$ $-1160$ $33.523$ $-2.8538$ $-13.957$ $-172.06$ $2.2462$ $-2.8519$ $9.3554$ $9.3554$ $2.962$ $-2.8508$ $-13.957$ $-172.06$ $2.346$ $-2.2642$ $-12.33$ $-4.5473$ $2.2460$ $-2.2642$ $-1.2047$ $-4.8159$ $2.2460$ $-1.2047$ $-4.8159$ $-2.9642$ $2.2460$ $-1.2047$ $-4.5199$ $-2.9642$ <			(				t	:	c	ţ
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Land cover Determinant	MFP Transformation	Corn	Soy bean	Winter wheat	Spring wheat	Cotton	Double crop	Grass	Forest
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3*log       -156.06         3       -10.925         107.93       -156.06         107.93       -0.5         108       -0.15         ~0.5       -19.925         ~1       73.284         ~1*log       81.575         ~1*log       81.575         ~1*log       73.284         ~1*log       81.575         ~2*log       72.851         ~3*log       72.851         ~2*log       72.851         ~2*log       11.189         ~2*log       -18.254         ~2*log       -17.066         ~2*log       -17.067         ~2*log       -17.067         ~2*log       -17.067         ~2*log       -17.067         ~2*log       -17.067         ~2*log       -17.09         <	Intercept		-42.159	-98.300	4.2869	-29.434	-157.15	-109.05	9.7262	14.705
3     -10,925       0g     -1       0a     -0.5       ~0.5     -19,925       ~0.5     -19,925       ~0.5     -19,925       ~1     73,284       ~1*log     81,575       ~1*log     30,523       ~2*log     72,881       ~1*log     11,189       ~2*log     72,881       ~2*log     11,189       ~2*log     -18,254       ~2*log     -11,09       ~2*log     -11,016       ~1     -11,019       ~2*log     -11,019       ~2*log     -11,016       ~2*log     -11,019       ~2*log     -12,013       ~2*log     -12,013       ~2*log     -12,013	Growing degree days / 1000	^3*log					-156.06		-4.9216	
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3*log     11.189     9.8554       ○3*log     -18.254     9.8554       ○2*log     -18.254     -4.5473       2*     -4.5473     -4.5473       2*     -4.5473     -4.5473       1     -2     17.018     -4.5319       57.453     67.493     117.99       1     -2.2*log     67.493     117.99       2     -1.1647     -1.3934     -1.106     -1.2047     -4.8159       2     1     -1.1947     -1.3934     -1.106     -1.2047     -4.8159       2     1     -1.1647     -1.3934     -1.106     -1.2047     -4.8159       2     -1.1647     -1.3934     -1.106     -1.2047     -4.8159       2     -1.1647     -1.3934     -1.106     -1.2047     -4.8159       2     -3*log     -41.81     -64.390     -631.49     5.5466       2     -412.77     -37.03     -475.73     -2.9542		~-2	30.523		-2.8598	-13.957		-172.06		-8.6125
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-412.77 $-475.73$ $-130.33$	Available water capacity	~3	-441.81		-64.390	-631.49	5.5466			
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Land cover Determinant MFP Transformation ^2*log ^1 ^0.5 ^-1 ^22	ttion Corn	Soy hean						
^2*log ^1 ^0.5 ^-1			Winter wheat	Spring wheat	Cotton	Double crop	Grass	Forest
^1 ^0.5 ^-1		-125.75						
~0.5 ^_1 ^-2								
^-1 2-2							6.2066	
Z-~						-0.1112		
								0.0455
^-2*log								0.0135
Soil pH / 10 ^3			2.6368					
^3*log			-66.753					
١~		5.9096		10.964				-9.5107
>-2	-0.6359				5.8103	4.9983	-0.3036	
^2*log					5.8907	5.0798		
Model performance								
Percent correct	0.818	0.778	0.722	0.914	0.912	0.842	0.655	0.787
Sensitivity	0.853	0.827	0.775	0.955	0.966	0.933	0.565	0.776
Specificity	0.783	0.729	0.668	0.873	0.858	0.752	0.744	0.798
ROC	0.901	0.859	0.828	0.965	0.934	0.900	0.711	0.869

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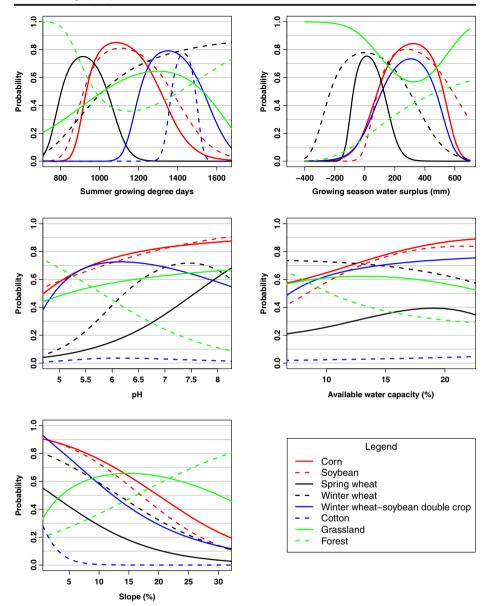
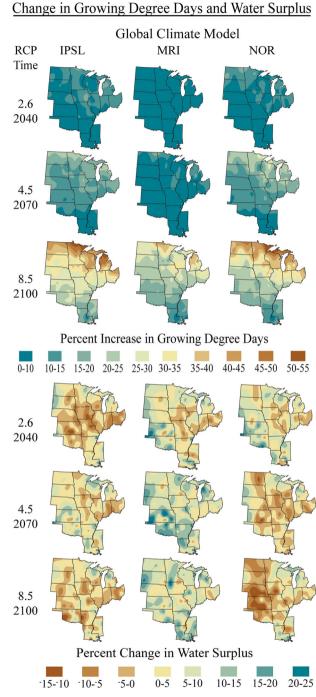


Fig. 1 Nonlinear response curves using multivariate fractional polynomials (MFP) of the eight land covers studied to their climatic, edaphic, and topographic determinants

## 3.2 Projected patterns of land cover changes

The downscaled climate projections reveal a substantial change in the spatial pattern of GDDs, with no decreases; for all three climate models, increases grow both over time and from south to north to a maximum of over 50 % (Fig. 2–top). There are substantial differences among the three climate models, with MRI projecting the smallest increase in summer GDDs and IPSL



**Fig. 2** Percent change versus historical conditions for each pixel in the study area under three climate scenarios: the MRI GCM in 2040 with RCP–2.6, the IPSL GCM in 2070 with RCP–4.5, and the NOR GCM in 2100 with RCP–8.5; (*top*) summer (June–August) growing degree-days (GDDs) (bottom) growing season (May–Sept.) water surplus

the largest. Changes in water surplus span a range from a 15 % decrease to a 25 % increase with less clear geographic or temporal trends and little agreement among the models (Fig. 2-

bottom). In contrast, Zhang and Cai (2013) show an increase in water deficits for rainfed crops in the central U.S. with negative implications for maize and soybean production globally.

Because of corn's narrow range of temperature preferences, the current geographical pattern of suitability for corn shifts perceptibly north under the low climate change scenario (MRI, RCP–2.6 in 2040), with a mean absolute change in logit value of 9 % on a pixel-by-pixel basis, and substantially north (22 % change) under the medium climate change scenario (IPSL, RCP–4.5 in 2070). Under the high climate change scenario (NOR, RCP–8.5 in 2100), the northern corn belt is reduced to marginal status with only a portion of northern Minnesota as highly suitable for corn (Fig. 3–top row). By 2070 under RCPs 4.5 and 8.5, two of the three climate models show southern losses exceeding northward gains; total area of central U.S. suitability declines from 36 to 67 % by 2100 under RCP– 8.5 under the three models (Fig. 4).

Soybeans, with its wider range of acceptable GDDs (Fig. 1), evidences a substantial, but less extreme, degree of northward migration in suitability (Fig. 3–row 2); note that percent change in pixel-specific logit values is slightly lower than for corn under each scenario. Soybean's decline in overall suitability is less than for corn in each scenario (Fig. 4); 29–55 % by 2100 under RCP– 8.5 under the three models.

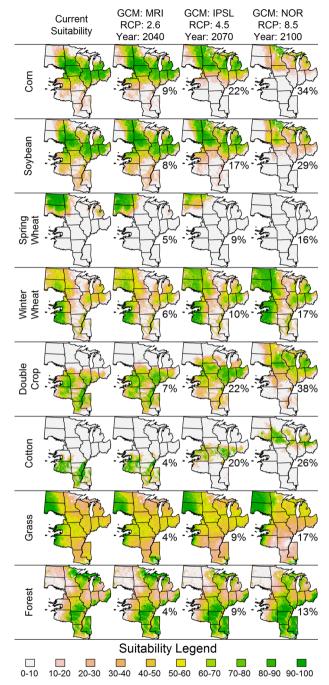
Suitable area is progressively eliminated from the central U.S. for spring wheat, with declines of 16 (MRI) to 38 (NOR) percent as early as 2040, even under RCP–2.6 (Fig. 3–row 3). The area of high suitability for winter wheat expands northward across the Great Plains while being maintained in the southern Great Plains (Fig. 3–row 4). Total area of likely occurrence increases in most climate change scenarios studied, including by 2040 under RCP–2.6, though with variation from 2 % using MRI to 27 % using IPSL. Under RCP–8.5 in 2100, the suitable area for winter wheat expands by 18 (MRI) to 50 (IPSL) percent (Fig. 4).

Demanding a long, warm growing season, double-cropping with winter wheat (usually Oct-June) and soybeans (usually June-Oct) is currently practiced on only 1 % of land in the central U.S. scattered in a belt north of cotton and south of corn-soybean rotations. In 2040 under RCP–2.6, suitable habitat for this productive cropping strategy expands by 15–25 % into the southern corn belt (Fig. 3–row 5), and by 5–33 % in 2070 under RCP–4.5 with a geographic distribution of suitability mirroring the current distribution for corn. By 2100 under RCP–8.5, there is high suitability for double-cropping in the northern half of the current corn belt with an expansion of 17–25 % relative to present.

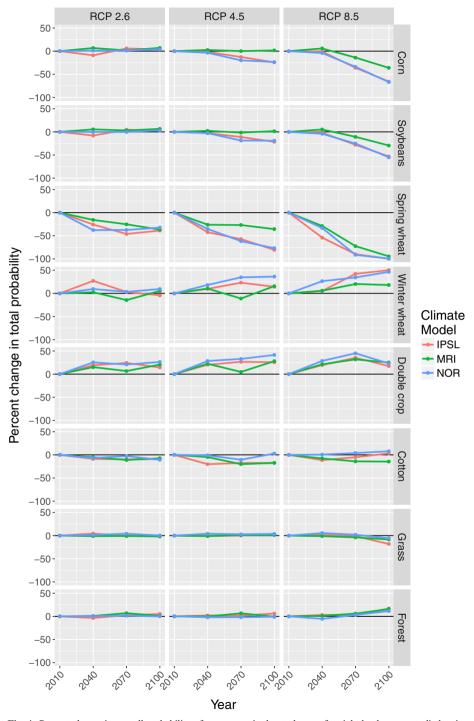
The suitable area for cotton, a warm climate crop with a narrow range of acceptable temperatures (see Fig. 1), migrates northward from its current limit at about 37° N, to reach central Minnesota at 46° N by 2100 under the high climate change scenario (NOR–RCP 8.5) (Fig. 3–row 6). Its total area of likely occurrence contracts slightly in 2040 and 2070, but expands by 2100 (Fig. 4).

Grasslands maintain a widespread suitable area (Fig. 4) while intensifying in drier areas in the western portion of the study area (Fig. 3–row 7). Intensification of forest in the southern part of the study area slightly overcompensates for being partially removed from northern lands that become more suitable for the crops studied (Fig. 3–row 8; Fig. 4). Subtropical crops in addition to cotton, winter wheat, and double-cropping, however, may become suitable on fertile lands in the southern portion of the study area. Detailed maps at 1 km resolution for each of the 27 scenarios for each of the eight land covers can be found in Supplementary materials on Pangaea (https://doi.pangaea.de/10.1594/PANGAEA.859593?format=html).

The quantity of spatial shift for a specific land cover is an indicator of the degree of adaptation to climate change that is required through such means as changes in land use or crop selection by location-bound farmers. This is quantified as the mean absolute change in Fig. 3 For each land cover, probability of occurrence maps based on, from left-to-right, current conditions, the MRI GCM in 2040 with RCP–2.6, the IPSL GCM in 2070 with RCP–4.5, and the NOR GCM in 2100 with RCP–8.5. The mean absolute percent change in logit value is shown as a measure of overall spatial shift. Maps at 1 km resolution for all scenarios studied are available from Pangaea (https://doi.pangaea.de/10.1594/ PANGAEA.859593?format=html)

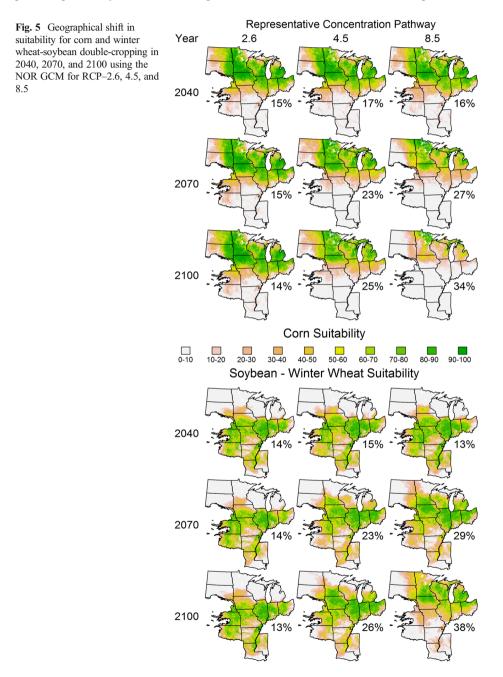


individual pixel-based logit values under current conditions compared to those under each climate change scenario (Insets in Fig. 3; Supplementary Table 2).



**Fig. 4** Percent change in overall probability of occurrence in the study area for eight land covers studied, using three climate models (MRI, IPSL and NOR), and three RCPs (2.6, 4.5, 8.5) in 2040, 2070 and 2100. This is a measure of overall expansion or contraction in the area of suitability within the central U.S. study area

Given corn's dominance as a highly productive and profitable grain (McPhail and Babcock 2008; Mehaffey et al. 2011) and raw material for the manufacture of innumerable agricultural and industrial products (Searchinger et al. 2008), it is valuable to examine the impact of varying intensities of climate change on its area of suitability more closely. Figure 5 (top) provides probability of occurrence maps for corn for 2040, 2070, and 2100 using the NOR



climate model, which generates geographic shifts greater than MRI, but smaller than IPSL. Geographic patterns under the three RCPs are not substantially different in 2040. By 2070, however, more effective mitigation of GHG emissions under RCP–2.6 compared to RCP–4.5, and RCP–4.5 compared to RCP–8.5, preserves large areas of corn suitability in the southern Corn Belt and greatly reduces the overall geographic shift (Supplementary Table 2). By 2100, only RCP–2.6 preserves a large area of corn suitability, while RCP–4.5 generates a corn suitability zone centered on Minnesota, and there is no identifiable U.S. corn belt under RCP–8.5. On a scenario-by-scenario basis, suitability for double cropping of winter wheat and soybeans improves where suitability for corn-soybeans rotations is diminishing (Fig. 5–bottom). Shifting to this cropping system thus serves as a possible adaptation to anticipated climate change.

While the future course of genetic adaptation of corn to changing climatic conditions is highly uncertain (Foley et al. 2011), the spatial analysis performed here can address the question of how much adaptation is needed in order to maintain current geographical patterns. This is derived as the change in GDDs that occurs in corn's current high suitability area under various climate scenarios. In the most extreme case, 2100 under RCP–8.5 using IPSL, corn would need to adapt to an increase of 361 GDD, giving it a temperature range warmer than that now observed for cotton (see Fig. 1), while by 2040 under RCP–2.6, corn would need to adapt by 47–120 GDD, and by 2070 under RCP–4.5 by 82–184 GDD, depending on the climate model used.

## 4 Discussion and conclusions

This analysis demonstrates that it is possible to derive a detailed projection of geographic shifts in the suitability for individual crops by combining statistical models of major land covers with statistical downscaling of AOGCM/ESM-derived climate projections. The methodology used is applicable for projecting the geographic suitability of crops in the U.S. and the world's other important agricultural regions where acceptable land use, soil, topographic, and climate data are available. For the U.S., the USDA/NASS Cropland Data Layer is ideal; as of this writing, coverage has expanded to 48 states (National Agricultural Statistical Service 2015).

The geographical analysis presented here represents *projections of suitability* for individual crops and land covers, assuming stationarity in determinants of suitability, not *predictions of land use patterns* in a dynamic world. The non-linear logistic regression models used to define suitability are fundamentally correlative, not causative. Many other causative factors of land use patterns that cannot be addressed in the framework employed here, from changing demographics, consumer preferences, environmental policies and producer outlooks to new crops and technologies, will also influence future land use patterns, and each of these factors introduces uncertainty into the projections. Other sources of uncertainty include the accuracy of the climatic, land use, and soil data used, errors in model specification, and the resulting stability of nonlinear logistic regression parameters.

Nonetheless, these projected geographic shifts in suitability have important implications globally, showing the possible decline of the central U.S. as a provider of, in descending order, spring wheat, corn, and soybeans to world markets, barring compensating genetic adaptations, and new opportunities for production of winter wheat. An expanded range of suitability for winter wheat-soybean double cropping, and to a lesser extent cotton, presents an opportunity to expand agricultural production, especially since suitability for these cropping strategies can replace corn-soybean production as its suitability zone shifts northward. Whether this and other opportunities for adaptation will be fulfilled, however, is dependent on the socio-economic factors raised above – including the availability of detailed information on emergent zones of suitability for specific cropping systems that this analysis helps satisfy, thus enabling adaptation.

Compared to previous studies of land use change in response to future climate change, this study is the first to provide crop specificity, in contrast for example to Sleeter et al. (2012), which uses "agriculture" and Sohl et al. (2014), which focuses on forest stand age. It also provides results at 30 m resolution, far exceeding the spatial detail provided, for example, by Sleeter et al. (2012) (U.S. ecoregions). Methodologically similar to the present study and sharing its high spatial resolution, the Sohl et al. (2012) study of future Great Plains landscapes indicates a shift from "natural" to "anthropogenic" land covers, with the degree of shift dependent upon IPCC SRES scenario. Their FORE-SCE models, while based on logistic regression of specific land cover categories, are not empirically validated, however, and lack crop specificity. With much greater spatial and crop specificity, this study supports Laingen (2012) and Wright and Wimberly (2013) findings that the corn belt is shifting northwestwards, and Zhang and Cai (2011) that the total U.S. area of agricultural suitability could expand – provided Siefert and Lobell (2015) observation about opportunities for increased double-cropping come to fruition.

These results are also important within the central U.S. region, where counties that rely on agriculture may find their economic base declining unless they are able to make major adaptations involving new or genetically modified crops or new cropping systems, while others, especially in a broad area bordering Minnesota and the Dakotas, will likely continue to experience opportunities for agricultural intensification. In all areas, land use and cropping patterns will need to adapt to both emerging threats and opportunities. Together with climatic changes themselves, these adaptations will bring with them substantial changes in natural resources such as water quantity and quality, and ecosystem service packages that each county or watershed is capable of generating.

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