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Key Points:

- We review ESM approaches to include agriculture, convergent modeled climate responses, and important development areas and uncertainties
- Improved ESM agricultural representations require benchmarking efforts to identify important regional components for climate impacts
- ESM development must focus on intensified agriculture, irrigation, and improved biogeochemistry to estimate carbon sequestration potential

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Representing agriculture in Earth System Models: Approaches and priorities for development

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Abstract Earth System Model (ESM) advances now enable improved representations of spatially and temporally varying anthropogenic climate forcings. One critical forcing is global agriculture, which is now extensive in land-use and intensive in management, owing to 20th century development trends. Agriculture and food systems now contribute nearly 30% of global greenhouse gas emissions and require copious inputs and resources, such as fertilizer, water, and land. Much uncertainty remains in quantifying important agriculture-climate interactions, including surface moisture and energy balances and biogeochemical cycling. Despite these externalities and uncertainties, agriculture is increasingly being leveraged to function as a net sink of anthropogenic carbon, and there is much emphasis on future sustainable intensification. Given its significance as a major environmental and climate forcing, there now exist a variety of approaches to represent agriculture in ESMs. These approaches are reviewed herein, and range from idealized representations of agricultural extent to the development of coupled climate-crop models that capture dynamic feedbacks. We highlight the robust agriculture-climate interactions and responses identified by these modeling efforts, as well as existing uncertainties and model limitations. To this end, coordinated and benchmarking assessments of land-use-climate feedbacks can be leveraged for further improvements in ESM's agricultural representations. We suggest key areas for continued model development, including incorporating irrigation and biogeochemical cycling in particular. Last, we pose several critical research questions to guide future work. Our review focuses on ESM representations of climate-surface interactions over managed agricultural lands, rather than on ESMs as an estimation tool for crop yields and productivity.

1. Introduction: The Importance of Incorporating Agricultural Management and Land-Use

Nearly 40% of Earth's land surface is now devoted to agriculture, managed for various cropping (Figure 1a), livestock grazing, or mixed farming systems [*Ramankutty and Foley*, 1999; *Foley et al.*, 2005; *Ramankutty et al.*, 2008]. The spread of agriculture has not been uniform with time, but has undergone rapid growth with expanding trade routes, new settlements, and technological advancements [*Ramankutty and Foley*, 1999; *Pielke et al.*, 2011; *Lawrence et al.*, 2016a]. This expansion has resulted in the large-scale modification of natural landscapes and ecosystems, ranging from land conversions to highly variable cropping and management patterns. These modifications and transitions alter important climate interactions, such as surface moisture and energy balances, and impact local, regional, and perhaps even the global, environment [*Pielke*, 2005; *Pielke et al.*, 2007a]. Early studies of agricultural land conversions and expansion have identified impacts on regional temperatures, surface energy partitioning, and rainfall variability [*Ramankutty and Foley*, 1999; *Feddema et al.*, 2005; *Foley et al.*, 2005]. Agricultural expansion has further been a main contributor to historical greenhouse gas (GHG, see Table 1 for full list of acronyms used herein) emissions, driven largely by deforestation, land degradation, and the disruption of soil layers [*Tilman*, 1999; *Lal*, 2003; *DeFries and Rosenzweig*, 2010; *Foley et al.*, 2011; *Arneth et al.*, 2017]. The very act of cultivation can also potentially impact regional suitability for agriculture by altering growing season temperatures, crop heat accumulation, surface roughness, evapotranspiration, and important vegetation-climate feedbacks [*Ramankutty et al.*, 2006]. It has even been suggested that the warmth of the preindustrial late Holocene can be partially attributed to early human modification of the land surface by way of agricultural production [*Ruddiman et al.*, 2015].

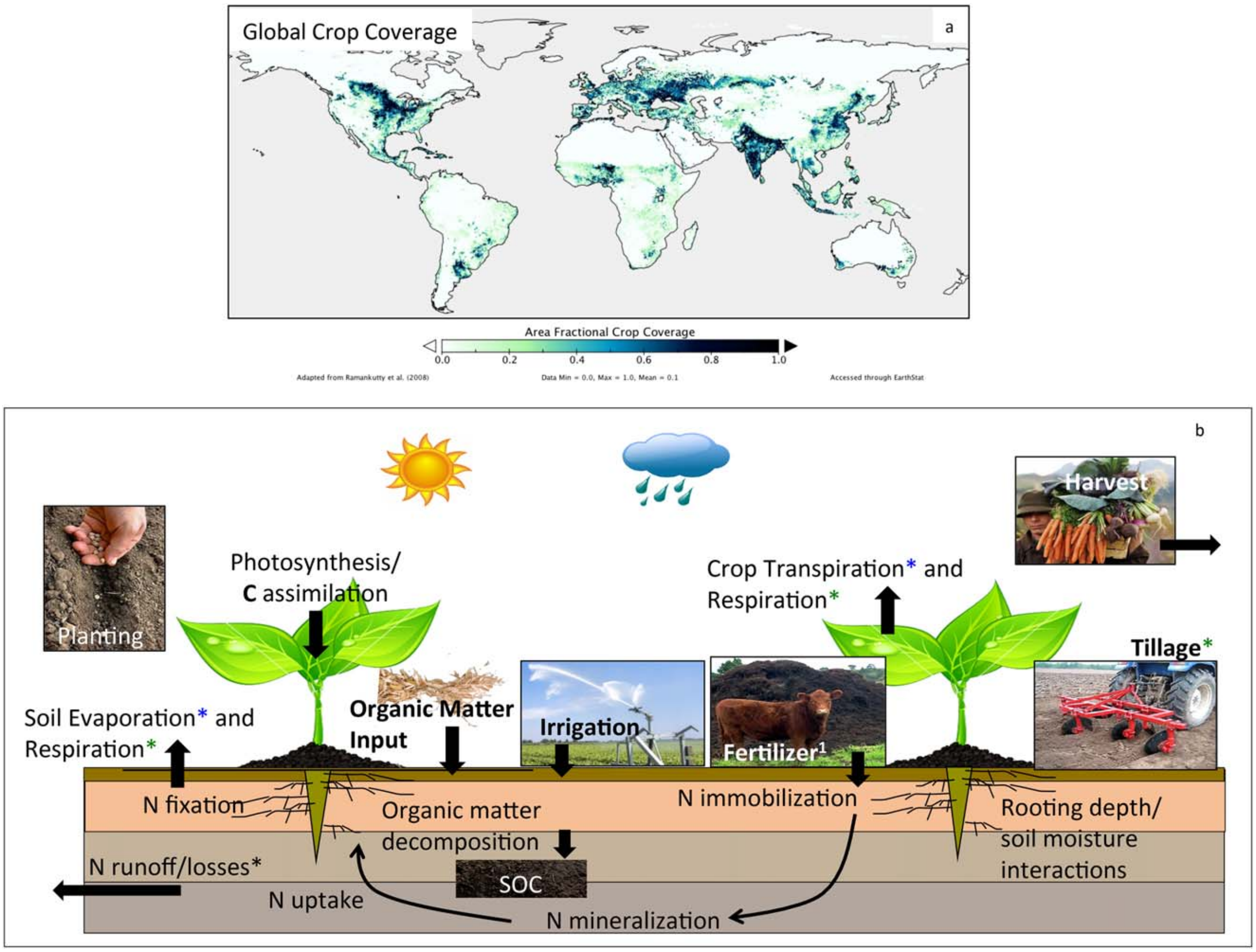

Figure 1. (a) Map of fractional area crop coverage (cropped areas only), adapted from *Ramankutty et al*. [2008], and obtained from the EarthStat database (http://www.earthstat.org/data-download/). (b) Cartoon illustration of the major agricultural components and management practices reviewed herein and that are important to represent in ESMs. Blue asterisks indicate water lost to environment; green asterisks indicate carbon lost to environment—major feedbacks pertinent to ESMs. Agricultural biogeophysical impacts result from many system components. Crop transpiration, height and aboveground structure (a contributor to surface roughness), albedo, and growth cycle (planting to harvest) can vary significantly from colocated natural vegetation. Unused Irrigation water can alter the attributes and saturation of the surface soil, impacting turbulent fluxes. Added crop residues—organic matter return—can alter soil evaporation and surface albedo as well. The biogeochemical impacts are also numerous. Crop growth and biomass production, respiration, and potential decomposition if added as residue, can impact carbon fluxes and soil carbon stocks. Likewise, the addition of nutrients, particularly nitrogen, for crop N-uptake can impact growth processes and residue decomposition. Unused nitrogen may also be lost or runoff from the system. Levels of tillage and land cultivation greatly modify soil carbon stocks (as well biogeophysical surface attributes). Furthermore, these systems vary temporally per human decision-making, such as through planting and harvest dates, which are generally weather-dependent. Overall, regional agricultural systems display much interannual variability, and ESM-targeted research questions must evaluate how much detail is necessary to capture the major climate responses and sources of uncertainty.

Over the 20th century, mechanization and industrialization greatly enhanced agricultural productivity and intensity. These gains were achieved through improved crop varieties with greater harvest indices (grain yield as a fraction of total biomass), the commercialization of inorganic fertilizers, and increased withdrawals of both surface water and groundwater for irrigation [*Evenson*, 2003; *Erisman et al*., 2008; *Gleeson et al*., 2012; *Pingali*, 2012]. Such technological advances have created a globally linked food system resulting in copious gains in food availability. However, industrialization also created a host of environmental concerns such as excess nitrogen runoff, increased GHG emissions, and groundwater depletion [*Hazell et al*., 1991; *Singh*, 2000; *Evenson*, 2003; *Pingali*, 2012]. Currently, global agricultural production and food systems now contribute to at nearly 30% of total GHG emissions, and constitute nearly 60% of non-CO_2 GHG emissions (e.g., CH_4, N_2O) [*Bustamante et al*., 2014; *Tubiello et al*., 2014]. The majority of these emissions result directly from intensive agricultural and livestock production, with significant contributions from deforestation and other land transitions [*Smith et al*., 2008; *Stavi and Lal*, 2013; *Tubiello et al*., 2014; *Herrero et al*., 2016].

Table 1. A List of Acronyms Used

Acronym	Full Phrase
ESMs	Earth System Models
LAI	Leaf Area Index
GHGs	Greenhouse Gases
CMIP6	Sixth Coupled Model Intercomparison Project
GCM	Global Climate Model
DGVMs	Dynamics Global Vegetation Models
IPCC	Intergovernmental Panel on Climate Change
LUCID	Land-use and Climate, Identification of Robust Impacts
LULCC	Land-use/Land Cover Change
PFTs	Plant Functional Types
RCPs	Representative Concentration Pathways
LUH2	Land-use Harmonization 2
LUMIP	Land-use Model Intercomparison Project

As such, more detailed representations of agricultural land-use and management in comprehensive Earth System Models (ESMs) are imperative to fully understand and quantify key regional and global climate forcings and feedbacks. In their initial development, ESMs represented agriculture simply as generic crop-like grasses (sometimes distinguished by photosynthetic pathway) with an annual growth cycle [*Levis*, 2010]. However, recent progress now enables ESM simulations to include specific crops, cropping cycles, and management practices, as well as their regional and/or global distributions [e.g., *Lokupitiya et al*., 2009; *Osborne et al*., 2009; *Levis et al*., 2012; *Drewniak et al*., 2013; *Cook et al*., 2014]. On-going and new model intercomparison efforts [e.g., *Lawrence et al*., 2016b] will help further direct and focus ESM development in representing agriculture, while identifying robust climate impacts. Additionally, more comprehensive data sets will greatly inform ESM agricultural representations and improve their utility for simulating agriculture-climate interactions.

Herein, we assess ongoing efforts to incorporate agriculture in ESMs, and suggest avenues for continued development and further lines of inquiry. Section 2 highlights key agriculture-climate interactions, including new emphasis to leverage agriculture in sequestering anthropogenic carbon.

Section 3 considers the simulated climate impacts of prescribed land cover changes in ESMs. Indeed, even these more simple, idealized agricultural representations reveal significant regional climate effects. Significant agriculture-climate interactions may also result from regional management practices. As such, section 4 describes work to incorporate a range of agricultural management in ESMs beyond idealized land conversions. Section 5 reviews the expanding body of work to incorporate dynamic agriculture into ESM land surfaces via modifications to land surface and vegetation/ecosystem models.

Augmenting this work is the important development of comprehensive ESM biogeochemical cycling, discussed in section 6. These developments will be critical to more fully investigate agriculture's potential carbon sequestration and impacts on biogeochemical cycling. As ESMs improve their agricultural representations, coordinated multimodel comparisons will better bracket uncertainties and identify key climate interactions. On-going and relevant coordination efforts, and their potential contribution to climate-agriculture assessments, are reviewed in section 7. Section 7 also provides a brief discussion on data needs and availability for model input and validation. Finally, in section 8 we suggest areas for focused model development, and raise key questions regarding climate-agriculture interactions.

2. Key Agriculture-Climate Interactions and Mitigation Potential

There exist several comprehensive reviews of the interactions between land-use and land cover changes (LULCC) and regional and global climate systems (illustrated in Figure 1b with elements particular to agriculture) [*Feddema et al*., 2005; *Foley et al*., 2005; *Ramankutty et al*., 2006; *Pielke et al*., 2007b,; *Levis*, 2010]. These interactions are often divided into two broad mechanisms: biogeophysical and biogeochemical. However, these mechanisms are interactive and when aggregated over space and time, they may serve to amplify or dampen each other's effects [*Seguin et al*., 2007; *Schurgers et al*., 2008; *Levis*, 2010]. For example, crop uptake of carbon dioxide via their stomata (a "biogeochemical" process) can also impact plant water transpiration (a "biogeophysical" process), thereby potentially altering surface energy partitioning. Several studies have discussed the broad spatial and temporal variation in LULCC-climate interactions, and highlight outstanding mechanistic uncertainties that warrant further investigation [*Pielke et al*., 2007a, 2007b; *Seguin et al*., 2007; *Levis*, 2010]. These include, but are not limited to: assessing the dominant drivers of moisture and energy balance, vegetation-aerosol effects, CO_2-vegetation interactions, competing biogeochemical and biogeophysical processes, and potential remote teleconnections resulting from land surface change.

Historically, agricultural expansion has been the dominant driver of LULCC, and thus the LULCC-climate interactions and concerns discussed above [*Foley et al*., 2005; *Pielke et al*., 2007a, 2007b; *DeFries and Rosenzweig*, 2010]. A significant portion of agriculture's environmental footprint can be attributed to its large-scale land appropriation from natural ecosystems, and subsequent land and habitat degradation [*DeFries and Rosenzweig*, 2010; *DeFries et al*., 2015]. These land transitions for agriculture are significant "forcings" on regional climates, temperature, and rainfall, although establishing robust responses is challenging, particularly at smaller spatial scales [*Foley et al*., 2005; *Lawrence and Vandecar*, 2014]. At larger scales, LULCC through agricultural expansion is known to be associated with a nontrivial radiative forcing, although outstanding data limitations on historical land transitions and associated emissions have led to quantification uncertainties [*Pongratz et al*., 2010; *Ward et al*., 2014; *Arneth et al*., 2017].

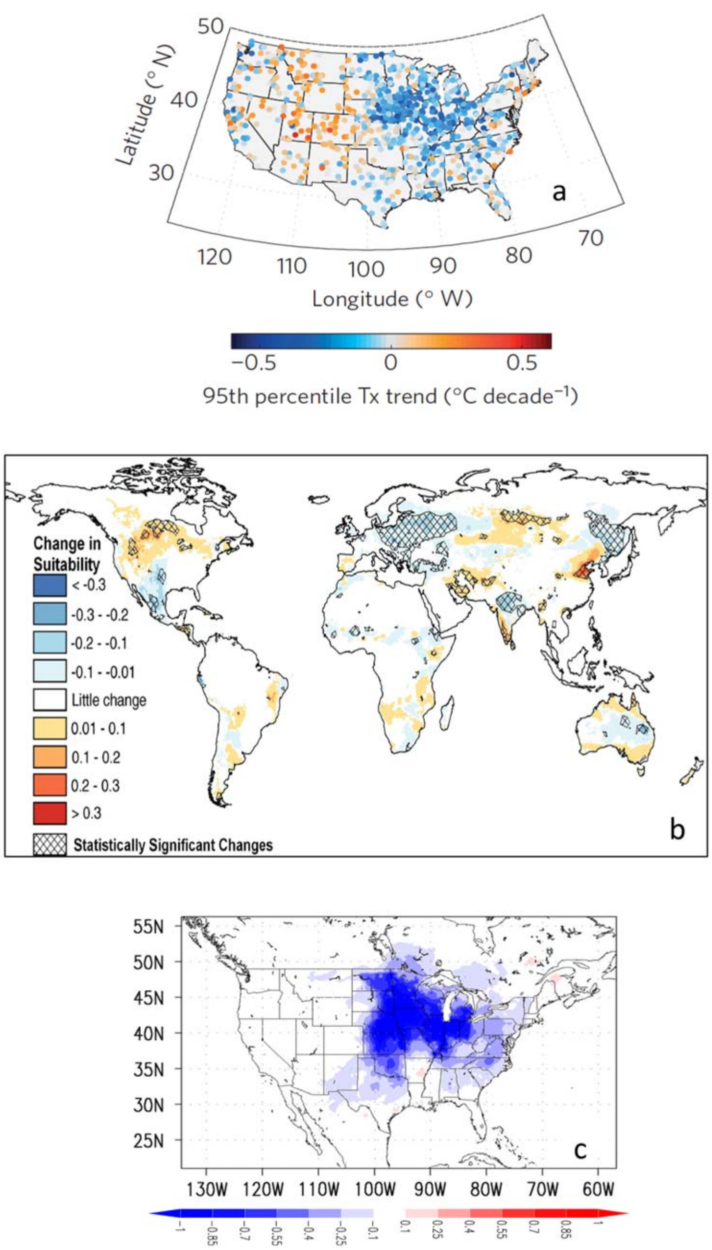

Figure 2. (a) Trend toward cooler daily maximum temperatures over the Midwest, which is more prominent during the hottest summer days, is thought to be in part due to agricultural intensification. From *Mueller et al*. [2015], Figure 2. (b) Change in suitability (to support agriculture) from potential vegetation conditions, with hatched areas showing significance. Negative change shows declining suitability. From *Ramankutty et al*. [2006], Figure 4. (c) Cooling shown for April–October, resulting from simulated differences in perennial biofuel crops (with adjusted rooting depth) versus conventional annuals. From *Georgescu et al*. [2011], Figure 1.

Constraining these climate-agriculture interactions becomes particularly salient as development increasingly intensifies alongside rising food, fuel, and fiber demands [*Foley et al*., 2011]. Furthermore, there is a need to make such development sustainable from both an environmental and food security perspective. There has been a host of recent observational and empirical work exemplifying how agricultural intensification impacts regional and global climates. For example, *Gray et al*. [2014] and *Zeng et al*. [2014] employed various data-based approaches, atmospheric inversions, and carbon accounting models to find that 20th century agricultural intensification has significantly amplified the seasonal atmospheric CO_2 cycle. Remote sensing analyses over the north China plains suggest that more intensive (double-cropped) systems could play a role in regional warming and enhance local aridity [*Ho et al*., 2012]. In fact, enhanced agricultural intensity and management, including irrigation, variety traits, and planting density, may drive cooling trends in summertime heat extremes in the U.S. Midwest [*Mueller et al*., 2015] (Figure 2a). These data-driven studies highlight both the biogeophysical and biogeochemical effects to be considered, along with their scale dependencies, in ESM simulations of modern agriculture [*Seguin et al*., 2007].

Finally, there has been much recent emphasis on utilizing agricultural management techniques to minimize, if not mitigate, GHG emissions [*Jawson et al*., 2005; *Liebig et al*., 2005; *Rosenzweig and Tubiello*, 2007; *Averett*, 2016; *Paustian et al*., 2016]. *Burney et al*. [2010] suggest that technological advancements leading to the current intensive production systems have prevented considerable GHG emissions, which would have otherwise resulted from extensification. This suggests that future intensification might be one avenue to minimizing agricultural GHG contributions. Additionally, there exist many localized studies evaluating the potential for agricultural land management to increase soil carbon stocks, and boost nitrogen and water efficiency [*Lal*, 2003, 2010; *Franzluebbers*, 2005; *Krishnamurthy et al*., 2009; *Lal et al*., 2011; *Bustamante et al*., 2014; *Paustian et al*., 2016]. These studies revealed considerable potential to reduce non-CO_2 GHG emissions and build carbon stocks through various management techniques. Such work can motivate site-specific recommendations for conservation strategies, and discussions of which strategies can be more widely adopted. These include soil conservation practices, more efficient fertilizer and water use in pasture and cropping systems, changing livestock feed for methane reductions from enteric fermentation, and changes in rice management to limit the effects of methane production in low-oxygen environments [*Lal*, 2003, 2010; *Franzluebbers*, 2005; *Krishnamurthy et al*., 2009; *Lal et al*., 2011; *Bustamante et al*., 2014; *Paustian et al*., 2016].

Quantifying agriculture's potential to mitigate climate change presents an interesting entry point for ESMs, and an opportunity to develop more comprehensive representations of agricultural processes (illustrated in Figure 1b). Improved ESM simulations may help identify efficacious management strategies to sequester anthropogenic carbon, while also incorporating important regional biogeochemical and biogeophysical feedbacks. However, other perspectives stress that there is both large variation in soil carbon sequestration potential and that more standardized data collection is needed to better understand soil biogeochemical processes [*Marland et al*., 2003; *Davidson and Janssens*, 2006; *Palm et al*., 2014; *Powlson et al*., 2014; *Paustian et al*., 2016]. At present, these processes are also underrepresented across the population of ESMs [*Todd-Brown et al*., 2013; *Luo et al*., 2016]. Some caution that the efficacy of some management techniques, such as no-till, to effectively mitigate anthropogenic carbon may be overestimated [*Powlson et al*., 2014]. Therefore, significant investments are needed in both model and data development before an accurate global quantification of agricultural mitigation capacity can be obtained.

3. Prescribed Representations of Croplands and Land Cover Change in ESMs

One of the main points of tension in ESM development is the perceived need to increase resolution and incorporate complex processes, while also optimizing simulation time and reducing uncertainties and sources of error. Thus, to quantify the impact of agriculture on regional climates while minimizing costly dynamical components, a number of studies have utilized simple prescribed, but skillful, ESM land surface representations of agriculture. The following example studies, summarized in Table 2, illustrate the resulting significant, and varied, simulated impacts on regional climate systems.

Ramankutty et al. [2006] used a semiempirical cropland suitability analysis in conjunction with the Community Climate Model version 3/Integrated Biosphere Simulator (CCM3-IBIS ESM) [*Delire et al*., 2002] to understand the climatic feedbacks that occur when natural landscapes are converted to croplands. The authors converted natural vegetation types to prescribed crop-like grasses, which resulted in the significant decline of cropland suitability in several regions, particularly in the required growing degree days and heat accumulation and the ratio of actual to potential evapotranspiration (Figure 2b). These results suggest that the very presence of agriculture in critical growing regions can alter the environmental conditions upon which it relies [*Ramankutty et al*., 2006].

Readily implementable, prescribed landscape conversions, in concert with other ESM operational capacities, have also been used to understand more extreme cases of environmental degradation resulting from agriculture. For example, *Cook et al*. [2009] modified the GISS ModelE global climate model (GCM) land surface over the US Great Plains domain to reduce the vegetation cover and introduce a soil aerosol dust source. When coupled with a specified La Niña sea surface temperature forcing, these simulations better reproduced the spatial extent of reduced rainfall and high temperatures during the 1930s "Dust Bowl" [*Cook*

Table 2. Simulated Climate Impacts of Agriculture With Various Earth System Models Components

Models Utilized	Region/Scale of Interest	Agricultural Feature Incorporated	Finding	References
Prescribed and/or Non-Interactive Implementations of Agriculture and Management				
COSMO-CLM RCM	Europe	Albedo/soil resistance modification for mulching and no-till agriculture	Cooling induced through representing no-till, and amplified on extreme heat days	*Davin et al.* [2014]
WRF	Central United States	Modified albedo, LAI, crop fraction for biofuels	Local to regional cooling; soil moisture depletion at depth	*Georgescu et al.* [2011]
MIRCO with MATSIRO	South and East Asia—Monsoon domain	Land cover transitions over 300 year period	Weakened monsoon and decreased rainfall	*Takata et al.* [2009]
ICTP RegCM3 with BATS	U.S. Midwest	Altered land cover distribution from potential vegetation to crops	Regional cooling; enhanced warm season precipitation	*Diffenbaugh* [2009]
GISS ModelE	U.S. Great Plains	Reduced vegetation cover and soil aerosol dust source	Land cover change amplified drought	*Cook et al.* [2009]
Noah LSM (standalone land-surface only)	CONUS United States	Irrigation, soil moisture deficit approach	Significant increases in ET, with higher increases in ET locally during growing season (particularly more water-limited areas)	*Ozdogan et al.* [2010]
LIS-WRF	U.S. Great Plains	Comparison of drip, flood, and sprinkler irrigation methods	Cooling and enhanced moisture downstream of irrigation; high dependency on irrigation type, land cover, and soil moisture anomalies	*Lawston et al.* [2015]
CLM4	CONUS United States	Irrigation, soil moisture deficit approach	Partitioning to latent heating more extreme in dry years	*Leng et al.* [2013]
NCAR/Penn State MM5/Noah LSM	California Central Valley	Irrigation, SMD approach modified with more representative soil water depletion and different model resolutions	Decreased temperature and enhanced RH; higher-resolution improves comparisons with data; effects are largely confined to irrigated areas	*Sorooshian et al.* [2011]
GISS ModelE GCM	South Asia—Monsoon Domain/Global	Irrigation, time-varying with offline calculated rates based on irrigated areas	Reduced monsoon circulation variability; reduced moisture transport over time; Dampens regional warming trends, significantly cools surface temperature as surface energy is partitioned toward enhanced ET	*Shukla et al.* [2014]; *Cook et al.* [2014]
HIRHAM5; HADRM3; RAMS; ECHAM/JSBACH	India	Model intercomparison of irrigation schemes	Enhanced ET, but reduced rainfall sub-regionally due to interactions with atmospheric circulation	*Tuinenberg et al.* [2014]
LMDZ/ORCHIDEE	Global	Irrigation rate determined by crop PFT requirements and soil moisture availability	In the US, regional increases are found in summer rainfall. Indian monsoon onset is delayed	*Guimberteau et al.* [2012]
RAMS	South Asia/India	Conversion from potential vegetation to cropland; irrigation taken as soil moisture under high rainfall conditions	Increased regional moisture flux; modified convective available potential energy; reduction in the surface temperature and modified regional circulation and rainfall	*Douglas et al.* [2009]
LMDZ	Global	Irrigation; flux applied as the observed contribution to global natural evaporation rate	Large surface cooling over irrigated lands, in contrast to radiative forcing increases	*Boucher et al.* [2004]
WRF with Noah-Mosaic	CONUS US	Irrigation applied at a prescribed rate and duration (based upon observed water pumping and availability) for the subgrid irrigated crop fraction when soil moisture falls below a prescribed threshold (i.e., irrigation applications dynamically responsive to low soil moisture conditions)	Strengthened high pressure systems over High Plains, and altered synoptic weather patterns. Reductions in precipitation over heavily irrigated areas, with remote increases in precipitation downstream	*Pei et al.* [2016]
Dynamic Implementations of Agriculture and Management				
CLM-Crop	Global	Crop PFTs with growth informed by AgroIBIS, fertilization	Improved GPP, crop productivity negatively correlated with temperature, and positively correlated with precipitation	*Drewniak et al.* [2013]
CLM4-CN with Crops	Global	Crop PFTs with growth informed by AgroIBIS	General reductions in latent heat flux, except around peak LAI; declines in peak summer precipitation in U.S. Midwest; improved model simulation of surface climate and NEE	*Levis et al.* [2012]
HadCM3-GLAM	Global	Crop PFTs; use of GLAM growth parameterizations	Increased growing season temperature variability; greatest impact in dry years with enhanced soil moisture deficits; semiarid to arid regimes are most sensitive to variations in crop growth	*Osborne et al.* [2009]
NCAR RegCM2 with BATS and CERES-Maize	U.S. Great Plains	Dynamic crop growth formulations from CERES-Maize incorporated into BATS surface energy and water balance calculations	Dry season exhibits enhanced partitioning to latent heat fluxes, and dynamic LAI also changed transpiration/evaporation partitioning of latent heat flux	*Tsvetsinskaya et al.* [2001]
Coordinated Assessments				
LUCID [ECHAM5; CCAM; CCSM; IPSL; SPEEDY; ECEarth; ARPEGE]	Temperate Regions (North America and Eurasia)	Varying agricultural representations and implementations	Altered turbulent fluxes, surface cooling in temperate regions, LULCC-climate responses depend on amount of deforestation	*Pitman et al.* [2009]; *Boisier et al.* [2012]; *De Noblet-Ducoudré et al.* [2012]
Comparison of CMIP5 Models [CanESM2; HadGEM2-ES; MIROC-ESM]	Global	Comparison of climate responses to LULCC change under RCP2.6 and RCP8.5, implemented per model configuration	General surface cooling; most significant effects occur when LULCC change exceeds 10% of area. Importance of LULCC forcing increases under the RCP2.6 scenario	*Brovkin et al.* [2013]

et al., 2009]. The soil aerosol dust source was a representation of the degraded soil conditions that had manifested during this time due in part to intensive agricultural management, which left soils uncovered as a result of crop failure, depleted of moisture and nutrients, and prone to erosion.

There has been much work focused on modifying land surface vegetation types and distributions in an effort to represent transitions between natural and human modified environments [*Avissar and Werth*, 2005]. Using the ICTP RegCM3 regional climate model with the Biosphere-Atmosphere Transfer Scheme (BATS) [*Dickinson et al.*, 1993; *Pal et al.*, 2007], *Diffenbaugh* [2009] replaced potential vegetation (that which would exist in the current climate conditions without human modification) in the United States with "modern" vegetation cover. This modern data set was informed by the Global Land Cover Characteristics Data, which captured the substantial areal crop coverage [*Loveland et al.*, 2000]. As a result of the modern crop cover, there was a significant summertime cooling over the Great Plains and Midwestern regions, resulting from changes in the Bowen ratio and albedo, respectively [*Diffenbaugh*, 2009]. The author additionally found that introducing crops enhanced lower atmospheric moisture content and availability and ultimately increased warm-season precipitation.

Though a cooling response in the U.S. Midwest was identified by both *Diffenbaugh* [2009] and *Mueller et al.* [2015], the suggested mechanism differed: conversion to crops versus enhanced intensification, respectively. Additional ESM modeling studies are required to further elucidate the agriculture-climate impacts identified in this region. Together these modeling and data-based assessments can help better identify and attribute the major mechanistic drivers of full agricultural land surface forcing.

There are also efforts to identify potential interactions between LULCC and synoptic-scale circulation features. For example, *Takata et al.* [2009] utilized a global historical vegetation map that reconstructed both natural and cultivated vegetation types, and therefore vegetative transitions, for the last 300 years. The authors implemented these time-varying vegetation transitions and included the appropriate parameters for each vegetation type (height, leaf reflectance, and photosynthetic parameters, though not constrained by their observed seasonality in the field), in the MIROC v3.2 GCM with the MATSIRO land surface scheme [*Takata et al.*, 2003]. They found that extensive cultivation decreased monsoonal rainfall and weakened monsoon circulation over the Asian domain, consistent with historical records over the studied timespan [*Takata et al.*, 2009].

A study by *Georgescu et al.* [2011] similarly modified the surface of Weather Research and Forecasting Model (WRF 3.1) coupled to the Noah land surface scheme [*Chen et al.*, 2001; *Skamarock et al.*, 2008] to better reflect crop characteristics, such as albedo, leaf area index (LAI), vegetation fraction, and rooting depth for biofuel crops commonly planted across the central United States. The authors additionally extended the duration of these crop characteristics to capture basic differences in phenology. These changes resulted in highly significant regional cooling, partially offsetting GHG-induced warming, and soil moisture depletion at depth due to enhanced rooting and evapotranspiration. The authors suggested that a better representation of such crops is necessary to fully characterize regional climate change, and that such effects should be incorporated into full cost/benefit evaluations of biofuel-driven land-use change [*Georgescu et al.*, 2011].

Modifications of ESM land surface characteristics to incorporate agricultural management do not have to be limited to representing vegetation. *Davin et al.* [2014] increased the surface albedo and scaled soil resistance to evaporation in the COSMO regional climate model v4.8 coupled to the Community Land Model (CLM) v3.5 [*Davin et al.*, 2011] to mimic the effects of crop residue mulch over European soils—a practice common to no-till and conservation agriculture. These changes, particularly increased albedo, acted to attenuate regional heat extremes [*Davin et al.*, 2014]. We note here that the CLM also has a dynamic crop simulation component, which was not employed in the above study, but is detailed in section 5.2 below.

Despite much work to incorporate prescribed (agricultural) land cover changes, much uncertainty still remains in identifying clear and robust climate responses. *Pitman et al.* [2009] conducted an early model intercomparison of land cover changes between 1992 and 1870, inclusive of crop and pasture area conversions. In general, the authors found that the imposed land cover changes induced climate responses of a similar magnitude but opposite to that of GHG-induced climate warming (cooling over converted areas). The temperature responses depended in part on the amount of deforestation [*De Noblet-Ducoudré et al.*, 2012]. These findings identify LULCC as another important anthropogenic forcing on regional climate systems. Perhaps more critically, however, the authors highlighted inconsistent responses among the seven climate models used, particularly related to: surface energy partitioning, the magnitude of surface temperature changes, and rainfall (detailed in Table 2) [*Pitman et al*., 2009; *Boisier et al*., 2012; *De Noblet-Ducoudré et al*., 2012]. The range of modeled climate sensitivities can be partially attributed to varying representations of land surface characteristics, such as parameterization of energy and moisture processes (i.e., ET), phenology, albedo, and land cover distributions [*Boisier et al*., 2012]. Such model intercomparisons are highly useful in demonstrating that land surface processes can account for a significant amount of regional climate uncertainty, and different model implementations can affect detection of robust climate responses. A full discussion on the utility of this effort and other coordinated model intercomparisons is provided in section 7.1 below.

The above studies show that agricultural impacts on regional climate processes may be broadly and efficiently represented by simplified, prescribed conversions between vegetation types and modifications to the land surface. Taken at scale, these representations show greater consistency with observational products (compared to natural or potential vegetation alone) and highlight important climate-agriculture interactions. Such representations are an important "first step" in assessing land surface controls on regional climate processes, and identifying climate sensitivity to human land-use. However, these experiments are highly idealized, using climatological annual cycles of plant growth that are not tied to actual management conditions, or generic "crop-like" grasses which do not necessarily have distinct, physiological crop-specific or crop-species attributes [*Levis*, 2010].

4. Specified and Implicit Representations of Agricultural Management in ESMs

The incorporation of agricultural management is simultaneously challenging, limited by the fidelity and accuracy of observed data sets, and necessary, as intraseasonal and interannual land management may greatly affect regional climate systems. Even the inclusion of basic agricultural attributes—crop coverage and large-scale management effects—can improve ESM simulations of important regional climate processes, such as surface turbulent fluxes and soil moisture coupling to temperature and rainfall. The following studies exemplify approaches to representing agricultural management in ESMs. However, a remaining challenge stems from trying to concurrently integrate multiple forms of management and their temporal variation into the same modeled environment.

4.1. Inclusion of Irrigation

The advent of large-scale irrigation, particularly from groundwater stores, has been a major contributor to increasing agricultural intensity, particularly in water-limited regions. Irrigation consumes nearly 70% of global water withdrawals, which account for $\sim$45% of global agricultural production [*Pokhrel et al*., 2016]. In some regions (such as South Asia), this rate can be as high as 80–90% [*Wisser et al*., 2008; *Rodell et al*., 2009]. Comprehensive reviews on the capacities, challenges, and emerging developments to include anthropogenic water resources in land surface representations are given by *Nazemi and Wheater* [2015a, 2015b] and *Pokhrel et al*. [2016]. The following discussion therefore summarizes just those model approaches incorporating irrigative demand, and the subsequent regional and global climate responses related to irrigation (see Table 3 in *Nazemi and Wheater* [2015a] for a list of "online" water resource formulations in land surface models). We then discuss the overall needs and outstanding challenges that exist in incorporating irrigation into ESM frameworks.

While fully interactive representations of irrigation, capturing time-varying crop management, do not yet exist in ESMs, approaches have been developed to estimate irrigation water requirement, and abstract this requirement from various available resources. Land surface models (LSMs) solve for the whole surface energy balance, allowing potential and actual transpiration, as well as the vertical distribution of soil moisture availability, to be directly calculated. These quantities can then be used in the computation of irrigation water demand, which is generally added to the system at the top vegetated soil layers in ESM gridcells. The ways in which modeling frameworks determine this demand can vary widely [*Nazemi and Wheater*, 2015a; *Pokhrel et al*., 2015]. Some consider the demand to be simply at or near field capacity (i.e., "soil moisture deficit" approach), which generally has little variation across most ESM agricultural areas. The irrigation demand is then satisfied by keeping the top soil layers at or close to this value, adding water (from an infinite source or surface stores usually) when moisture levels fall below a specified amount [*Saeed et al*., 2009; *Pokhrel et al*., 2012, 2016; *Tuinenburg et al*., 2014; *Nazemi and Wheater*, 2015a, 2015b]. Other studies have blended

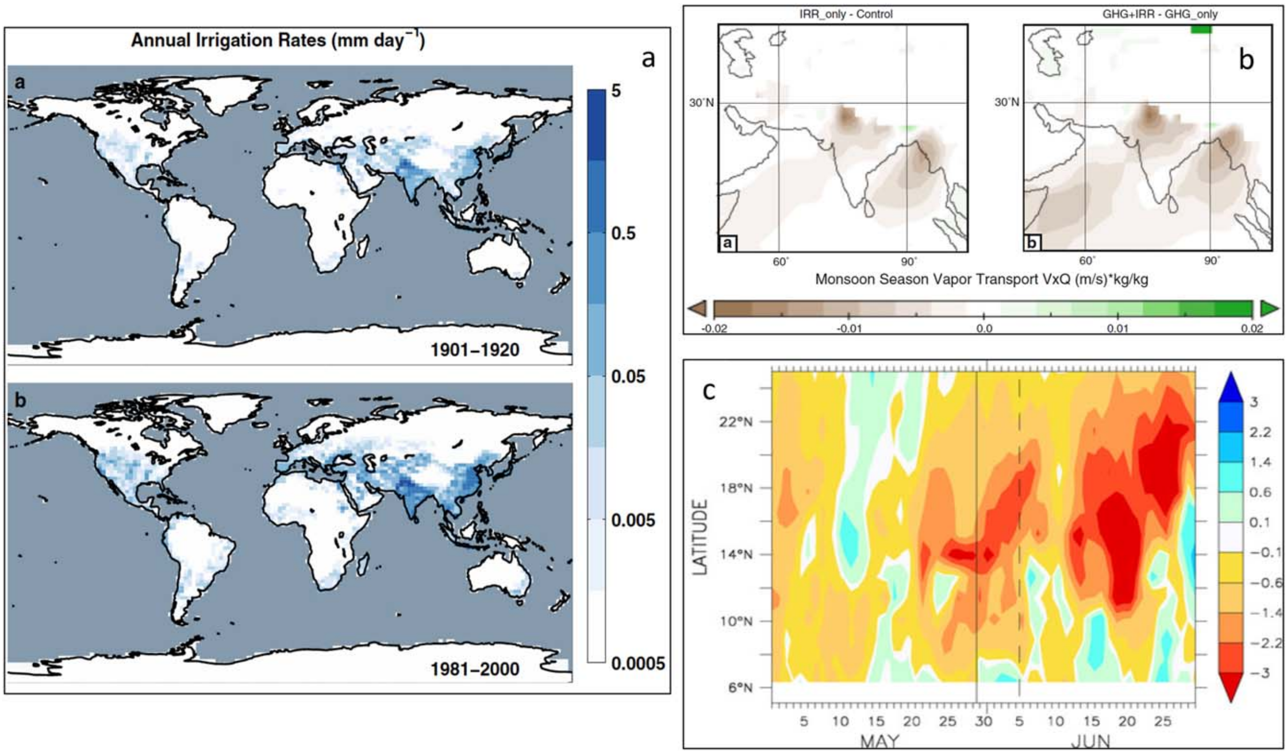

Figure 3. (a) Annual irrigation rates from (top) 1901 to 1920 and (bottom) 1981 to 2000, the latter showing both areal expansion and intensification of irrigation. From *Cook et al*. [2014], Figure 1. (b) Simulated decreases in monsoonal (June–September) moisture transport (from control simulations) over the South Asian Summer Monsoon domain as a result of irrigation. From *Shukla et al*. [2014], Figure 10. (c) A Hovmöller diagram for the South Asian Summer Monsoon longitudinal domain, showing the daily differences in rainfall between irrigated and nonirrigated simulations. Irrigated simulations show a delay in the monsoonal rainfall onset from the Monsoon Onset over Kerala. From *Guimberteau et al*. [2012], Figure 16.

data-based assessments and results from offline hydrological modeling to create a monthly time series of irrigation rates spanning the 20th century for the whole world (Figure 3a) [*Döll and Siebert*, 2002; *Freydank and Siebert*, 2008; *Wada et al*., 2014]. The implementation of these data sets can enable improved (albeit implicit) representations of regional agricultural heterogeneity [*Puma and Cook*, 2010; *Cook et al*., 2014; *Shukla et al*., 2014]. These implementations include water applications to compensate for climate-induced soil moisture deficits, and even an explicit treatment for flooded conditions under rice paddy cultivation.

As ESMs further develop their agricultural representations, more crop-specific irrigation implementations have emerged based on a crop type or growth. In these cases, a scaling factor adjusts crops' time-evolving potential evapotranspiration, which along with the available water, determines the necessary irrigation requirement [*Döll and Siebert*, 2002; *de Rosnay et al*., 2003]. *Nazemi and Wheater* [2015a] also noted irrigation representations that consider CO_2 fertilization effects on crop growth, which could modulate the effects of crop water productivity. This has further potential to modify transpiration and, thus, the irrigation requirement [*Deryng et al*., 2016]. Such an algorithm was implemented in the Lund-Potsdam-Jena managed Land model, for example [*Bondeau et al*., 2007]. *Ozdogan et al*. [2010] have developed a crop-specific implementation of irrigation water demand for the United States within the Noah LSM that further accounts for the type of irrigation method used. Incorporating this methodology further reduced surface climate biases and improved forecast skill [*Ozdogan et al*., 2010].

In general, these studies generally show that added irrigation water to the surface reduce the Bowen ratio by increasing regional latent heating (summarized in Table 2), and also result in increased atmospheric moisture content over irrigated areas, although direct impacts on rainfall and cloud formation vary regionally and are less conclusive [*Tuinenburg et al*., 2011, 2014].

However, climate responses to irrigation are particularly acute and robust in semiarid to arid environments, such as the South Asian Summer Monsoon domain [*Boucher et al*., 2004; *Douglas et al*., 2009; *Puma and Cook*, 2010; *Tuinenburg et al*., 2011, 2014; *Cook et al*., 2014; *Shukla et al*., 2014]. *Lucas-Picher et al*. [2011]

conducted a regional climate model intercomparison over the South Asian monsoon domain, and suggested that identified precipitation biases may be, in part, attributed to the lack of regional irrigation representation. As one of the most heavily irrigated regions on Earth, semiarid to arid South Asia appears to experience strong synoptic and climatic effects due to the introduction of irrigation, including a weakening of the monsoon circulation, reduced moisture transport, delayed onsets, and a redistribution and/or reduction of rainfall (Figures 3b and 3c—see Table 2 for complete list of models utilized per study) [*Boucher et al*., 2004; *Douglas et al*., 2009; *Saeed et al*., 2009; *Lucas-Picher et al*., 2011; *Guimberteau et al*., 2012; *Shukla et al*., 2014; *Tuinenburg et al*., 2014]. These studies reflect an emerging consensus that representing intensive irrigation in South Asia is necessary, along with other anthropogenic forcings, to best reproduce its historical climatology and regional variation in monsoon strength, surface fluxes, and even subregional rainfall distribution and timing.

In addition, simulations using the NCAR/Penn State mesoscale model (MM5) coupled to the Noah LSM with irrigation [*Chen et al*., 2001] resulted in increased precipitation and substantial changes in surface energy partitioning in California's Central Valley. Observational evidence also exists for such an effect over the Great Plains growing region [*DeAngelis et al*., 2010; *Sorooshian et al*., 2011]. In contrast, experiments using the WRF/Noah-Mosaic land surface modeling approach with dynamic irrigation [*Li et al*., 2013] resulted in reduced rainfall over the US High Plains, and downwind precipitation increases in more remote locations [*Pei et al*., 2016]. These regional-scale studies are critical to understanding the spatially varying impacts of irrigation, particularly across regions with large rainfall gradients.

More generally, the multitude of climate-irrigation studies to date indicates that widespread irrigation generally introduces significant regional, and even a global, climate signals [*Cook et al*. 2014]. For example, *Cook et al*. [2014] used the GISS ModelE global climate model to show that irrigation appears to "mask" the regional GHG-induced warming signal, particularly in the most water-limited, but highly productive, areas. As such, the authors recommended that irrigation should be considered as part of the suite of historical forcing agents considered with coordinated climate assessments.

More generally, the inclusion of human-water interactions—in the form of water resources and balances for important reservoirs—is a fundamental component of agriculture. In light of the above findings, irrigation may be a substantial component of the overall agricultural "land-use forcing," particularly in South Asia, major United States growing regions, and generally across high producing, water-limited regions. Thus, future attempts to include agriculture in ESMs and quantify its climate impacts must also include a representative irrigation scheme.

However, *Nazemi and Wheater* [2015a, 2015b] and *Pokhrel et al*. [2016] provided detailed discussions regarding some important areas of needed improvement relevant to ESM development. First, irrigation demand ultimately depends on the crop water demand, and thus regional climate simulations would benefit from improved representations of cropping system heterogeneity. This includes more representative cropped grid fractions for irrigation applications; prescribing crop-specific growth, transpiration, and water productivity attributes (e.g., using crop-specific plant functional types, discussed below); or more dynamic, climate-responsive, crop formulations (discussed below). Yet, for current ESM resolutions, representing agricultural heterogeneity would potentially demand an added level of detail and complexity in the subgrid-scale processes included. In addition to crop growth attributes, the crop growing season and phenology will be critical to define, such that irrigation is appropriately seasonally constrained. Prescribing these attributes in ESMs is limited by the availability of time-varying global and regional data sets, which do not adequately capture inter or intraseasonal variation. Furthermore, more dynamic crop growth formulations are subject to uncertainties in their adopted rules for planting/harvest and growth parameterizations in response to climate conditions [*Nazemi and Wheater*, 2015a].

Second, better representations of regional soil attributes, which can impact water retention and availability, and groundwater stores could help to better constrain irrigation water demand over longer timescales. While some LSMs include representations of groundwater pumping and other water abstractions for irrigation, current representations and interactions are still highly simplified [*Nazemi and Wheater*, 2015b; *Pokhrel et al*., 2015, 2016]. Additional improvements are needed in the temporal and spatial representation of surface water reservoirs, particularly those created in response to fulfilling intensive irrigation demand (e.g., dams and other man made containments and diversions). These could substantially alter local to surface energy partitioning and balance, leading to interactions with regional climate systems [*Nazemi and Wheater*, 2015b; *Pokhrel et al.*, 2015, 2016].

Last, the fidelity of irrigation representations in ESMs will depend upon the quality and the temporal and spatial coverage of available data. For example, global inventories exist for irrigated areas, but such data are more reliable for industrial agricultural zones than for heterogenous cropped areas in developing countries, where there can be significant gaps in data and information [*Nazemi and Wheater*, 2015a; *Pokhrel et al.*, 2016]. Such data sets can therefore introduce uncertainty in climate model simulations. Additionally, comprehensive global and regional data sets to indicate the type of irrigation, in addition to the amount and timing of application, are still largely unavailable. This presents an important limitation, as such information may be important to fully capture the agriculture-climate interactions over high production zones. For example, *Lawston et al.* [2015] utilized the Weather Research and Forecasting (WRF) model coupled with an irrigation implementation and found a high degree of regional climate sensitivity in the US Great Plains to the method of irrigation (drip, sprinkler, and flood) employed.

The data sets that are available, obtained from census or inventory-based products or through offline model derived estimates, are subject to much uncertainty in their collection and creation, lack of agreement, and/or inconsistent coverage in space and time [*Nazemi and Wheater*, 2015a]. For example, *Leng et al.* [2013] attempted to simulate irrigation water demand over the coterminous United States with the Community Land Model (CLM) 4.0. The authors found that inconsistencies and variability between the existing data sets used for comparison exceeded the interannual variability of the model simulations. Such discrepancies, even in quite developed and highly documented growing regions, can make model and process validation tenuous and requires enhanced calibration of model parameter values. This could possibly introduce other biases and/or make more generalized or global simulations more challenging.

4.2. Timing of Agricultural Management: Phenology and Cropping Calendars

More conventional crop representation in ESMs generally utilize generic grasses with crop-like attributes and a leaf area index (LAI) curve similar to natural vegetation with an annual growing cycle. Other studies have incorporated remote-sensing-based LAI information, which help to better represent observed evapotranspiration from the surface and the partitioning of latent and sensible heat fluxes [*Chase et al.*, 1996; *Buermann et al.*, 2001]. These representations are challenging to implement due to difficulties obtaining a clear crop-specific LAI signal in heterogenous growing regions with many land cover classifications. However, improved attempts to constrain crop-specific LAI by crop-specific calendars will offer ESM users a range of capacities. These include the ability to evaluate the differences between physical attributes of managed landscapes and natural vegetation; ascertain the regional climate effects from management systems in which crops tend to have different growth cycles than their natural counterparts; and also allows for the simulation of crop rotations or multiple croppings in a specific grid cell within a given year.

While crop planting and harvest dates are influenced by a range of nonclimatic factors and decision-making, they are closely related to environmental variables, particularly in rainfed regions. *Sacks et al.* [2010] produced a global data set of planting and harvest dates for major crops, and identified strong correlations between the distribution and growth of temperate cereals and key environmental variables. Such data sets are useful to constrain regional crop growing seasons in ESM land surfaces, allowing for more accurate representations of phenological development and resulting climatic feedbacks. For example, these planting and harvest date data sets can be used in conjunction with more representative maps of crop coverage to construct global gridded maps of crop-specific timing. These are then readily implemented and prescribed in ESM land surface frameworks. An example is shown in Figure 4 using the global coverage of maize, wheat, rice, and soybean from *Monfreda et al.* [2008] and planting and harvest dates specified by *Sacks et al.* [2010]. LAI maxima taken from remote sensing products for various crops (e.g., LAI3g) [*Zhu et al.*, 2013] can help to constrain crop-type, and even potentially crop-specific, LAI evolution and prescribe regional cropping cycles in ESM land surface components. A more dynamic approach is presented by *Deryng et al.* [2011] and *Waha et al.* [2012], who have similarly established relationships and rules for planting based upon key regional agroclimatic variables which determine and limit crop growth, such as temperature and heating thresholds needed for critical growth stages and measures of crop available soil moisture [*Deryng et al.*, 2011; *Waha et al.*, 2012]. These rules were implemented into crop modeling frameworks, and the resulting simulations of crop growth and phenological development were in good agreement with observations–

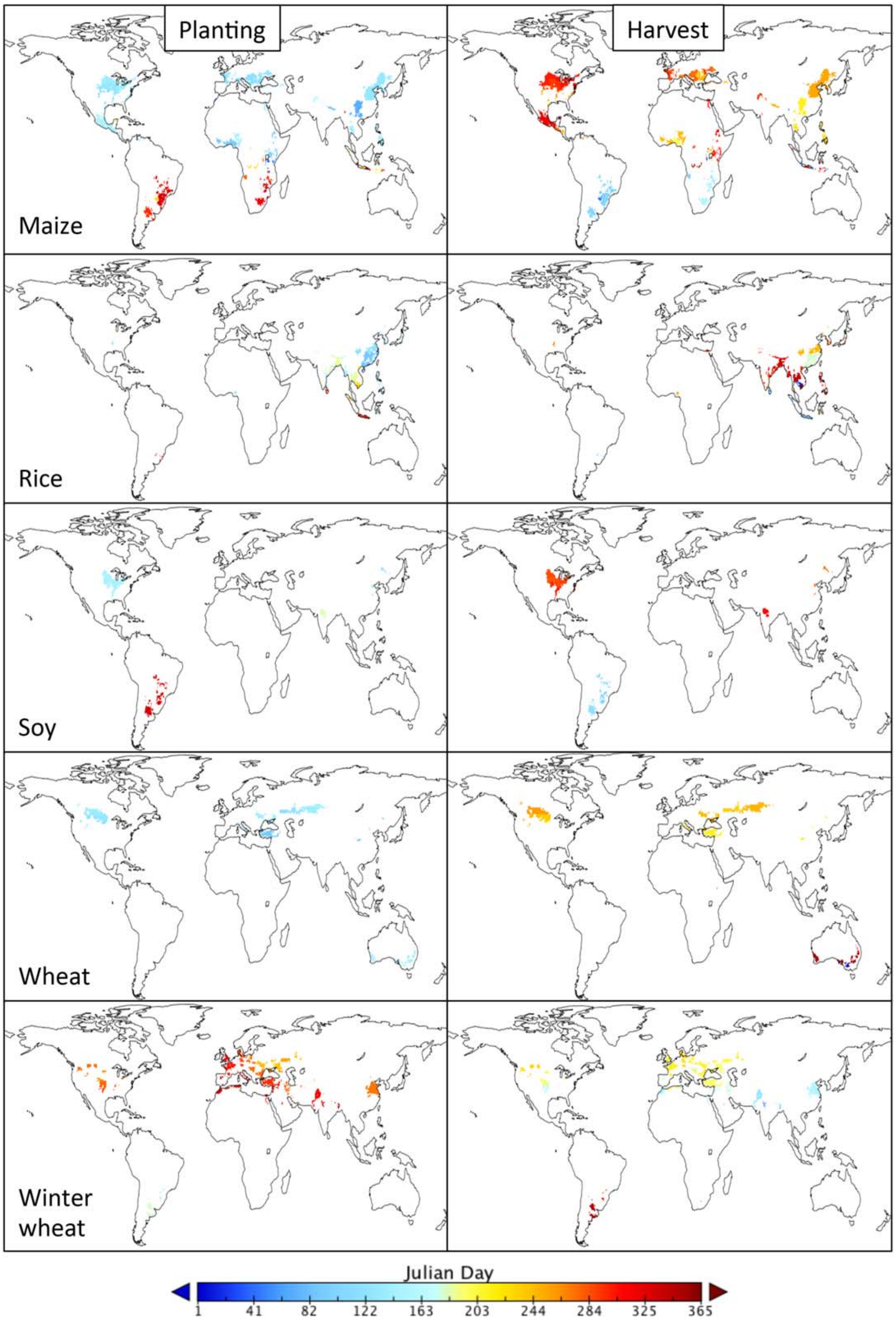

Figure 4. Planting and Harvest dates for maize, rice, soybean, and wheat. Maps were created by masking the *Sacks et al*. [2010] cropping calendar data set with crop-specific fractions from the *Monfreda et al*. [2008] crop distributions data set, aggregated to a resolution of 0.5° × 0.5°. Such data sets are useful for improving the spatial representation of agriculture in ESM, particularly those that have PFTs with crop-specific attributes, either dynamic or prescribed.

these developments can further aid in better representation of seasonal cropping cycles for more dynamic ESM simulations of agriculture, discussed below.

4.3. Evaluating Environmental Impacts of Prescribed Agricultural Emissions

The above studies consider mostly the biogeophysical impacts of prescribed agricultural representations. Yet, equally important are the biogeochemical interactions and fluxes between the soil, crops, and management, and the overlying atmosphere. For example, regular tillage and disturbance of agricultural soils pre and postharvest can oxidize soil carbon, leading to a loss of soil fertility and substantial carbon emissions (further exemplified in section 6.1) [*Snyder et al*., 2009; *Stavi and Lal*, 2013; *Tubiello et al*., 2014]. Methane emissions associated with paddy cultivation and flood irrigation comprise ~10% of total global (anthropogenic) methane emissions and thus constitute an important global forcing (with other large contributions originating from the livestock sector) [*Snyder et al*., 2009; *Dlugokencky et al*., 2011; *Höglund-Isaksson*, 2012]. While there have been recent developments to incorporate improved wetland hydrology in ESMs [*Fan and Miguez-Macho*, 2010; *Collins et al*., 2015a, 2015b], most climate models currently underrepresent the soil biogeochemical interactions important to simulating wetland GHG emissions [*Bradford et al*., 2016; *Pokhrel et al*., 2016]. Additionally, excessive applications of nitrogen-based fertilizers and manure management have lead to increasing N_2O emissions over the 20th century and have further exacerbated regional air pollution and nutrient runoff into aquatic systems [*Lelieveld et al*., 2015; *Stavi and Lal*, 2013; *Bauer et al*., 2016]. Complete simulations of agricultural biogeochemical impacts require the integration of more interactive carbon and nitrogen models (further discussed in section 6).

However, current emissions inventories for climate simulations do include pollutants from global food systems. *Bauer et al*. [2016] used the GISS ModelE2 ESM with an aerosol microphysics scheme to examine the individual and combined effects of ammonia produced through fertilizer use and livestock production and nitric oxide created from combustion. These species may contribute to the formation of secondary inorganic aerosols—a major constituent of $PM_{2.5,}$ which is harmful to human health. The authors found that agriculturally derived air pollution, associated with the overuse and overproduction of nitrogen inputs, dominated over other forms of anthropogenic pollution, including fossil-fuel combustion [*Bauer et al*., 2016]. These pollutants also impact some of the most heavily populated areas, and therefore are important to resolve and attribute in ESMs. This is particularly urgent as many developing regions increase their agricultural intensity practices and increased livestock production. Such effects can be substantially altered by management practices, crop types, and interactions with other key components of agricultural systems, and so there is utility in considering how these emissions may be modulated (or exacerbated) in more dynamic ESM frameworks with an explicit treatment of nitrogen, and broader biogeochemical effects.

5. Representing Agriculture Through Dynamic, Coupled Climate-Crop Models

ESM simulation of regional climates has improved by using more comprehensive prescriptions of LULCC to represent agriculture. However, prescribing average or "snapshot" crop distributions and management fall short of capturing the great deal of temporal and spatial variation in agricultural responses to climate conditions. For example, planting/harvest dates, irrigation and nutrient applications, crop productivity and water use efficiency, soil carbon stocks, and even whole cropping systems can display substantial amounts of interannual variability. Therefore, simulating dynamic agroecosystem responses would allow for improved simulations of time-varying climate conditions, rather than mean climatologies. Dynamic crops and management also enable transient simulations to assess the impacts of agricultural transitions, and the efficacy of management changes to improve soil health and sequester carbon. The following sections detail efforts to incorporate dynamic crop responses and management in ESM frameworks, and highlight the potential to include agroecosystem management as a transient anthropogenic climate forcing.

5.1. Incorporating Crop Growth Into ESMs via Land Surface and Vegetation Models

Levis [2010] provided a comprehensive overview of the evolution and utility of Dynamic Global Vegetation Models (DGVMs) to simulate important components of biogeochemical cycling and time-varying biosphere-climate feedbacks. Many of these models utilize plant functional type (PFT) frameworks, which group plant species with similar phenological and physiological attributes and assigns to them functionality responsive to evolving climate conditions. Most DGVMs adopt recommendations by *DeFries et al*. [1995] to distinguish physiogonomic characteristics: growth form (woody, herbaceous), photosynthetic pathway, leaf type (e.g., needleleaf), and phenotype (e.g., evergreen, cold deciduous, drought deciduous; for herbs, annual versus perennial), often with C3/C4 generic grasses to represent crops. PFTs that share the same soil fraction and column respond to environmental growing conditions and can compete for resources. More generally, this approach enables simulation of a range of ecosystem dynamics relevant to regional climate processes [*Levis*, 2010]. A more complete description of PFT attributes can be found in *Levis et al.* [2010], and references therein. While the increasing complexity of DGVMs (or, generally, LSMs with dynamic vegetation) has been a major recent advance, incorporating agriculture and management into a similar framework in the context of ESMs poses additional challenges.

In general, LSMs require information about plant types, distributions, growth, and lifecycle processes in order to solve for land surface energy and water balance, nutrient stocks and flows, and exchanges of these important quantities with the climate system. Principle to this is the simulation of plant carbon assimilation, respiration, and transpiration of water. Many current LSMs use adaptations of the Faquhar-Ball-Berry model of coupled leaf-level photosynthesis and stomatal conductance—the solutions to which have proven robust for a range of environmental conditions—and a variety of scaling techniques to canopy level [*Farquhar and von Caemmerer*, 1982; *Ball et al.*, 1987; *Collatz et al.*, 1991; *Cox et al.*, 1998; *Lawrence and Slingo*, 2004; *Lokupitiya et al.*, 2009; *Oleson et al.*, 2013; *Kim et al.*, 2015; *Liu et al.*, 2016]. Solving for photosynthesis and conductance requires numerous PFT-specific parameters, examples of which are shown in *Kim et al.* [2015] for four PFTs in the Ent Terrestrial Biosphere Model, Table D1 [*Farquhar and von Caemmerer*, 1982; *Ball et al.*, 1987; *Collatz et al.*, 1991; *Luo et al.*, 2012; *Oleson et al.*, 2013; *Kim et al.*, 2015]. Several coupled climate-crop models, reviewed in section 5.2 below, have leveraged these existing LSM formulations for conductance and/or photosynthesis by introducing crop-specific PFTs or appending crop growth models. This requires obtaining the appropriate parameters for representative simulations of crop-specific carbon assimilation and transpiration rates. However, such parameters are often site-specific, obtained for data-rich and highly productive growing regions, and there can be difficulty establishing values outside these areas.

Simulating dynamic crop growth in climate models also requires crop-specific parameterizations of phenology and allometry, which can differ substantially from natural PFTs. Crop PFTs are distinctive from natural vegetation in that they usually explicitly include separate key growth phases. These broadly include (and are not limited to): planting, emergence, vegetative growth, grain fill (in which carbon is reallocated to maximize the harvest index), maturity, and harvest. These parameterizations generally have dependencies on temperature, and use various growing degree day or heat accumulation formulations to determine the time to and the duration of particular growth phases. Many such crop PFTs and/or growth models have been developed, and can be as general as "temperate cereals" or as specific as oil palm [*Bondeau et al.*, 2007; *Osborne et al.*, 2007; *Lokupitiya et al.*, 2009; *Levis et al.*, 2012; *Fan et al.*, 2015; *Liu et al.*, 2016]. For example, the Lund-Potsdam-Jena managed Land model (LPJmL)—a standalone DGVM—explicitly includes 13 agricultural PFTs, including 11 crops, and two managed grass types [*Bondeau et al.*, 2007]. Some crop PFT and process formulations account for over 100 parameters, which can vary regionally and/or by crop species—examples for which are given in Tables 20.1 and 20.2 in *Oleson et al.* [2013] and [*Bilionis et al.*, 2015]. Differences between LSM crop growth representations may stem from the intended spatial scale of study (or from which growth parameters was obtained), the level of detail of specific crop species' simulated development (e.g., the number of growth stages), and/or the variety of processes incorporated (such as CO_2 fertilization effects).

There already exist numerous "point-based" crop models, intended to operate at the field or plot scale. These models require well-defined management schedules (nutrients, irrigation applications, and sowing windows) and variety traits, and highly resolved weather, both temporally and spatially [*Jones et al.*, 2003; *Keating et al.*, 2003; *Asseng*, 2013]. These crop models were developed within the agronomic community to estimate yields, assess growth sensitivity to weather, and evaluate new and/or alternative management strategies—analyses that have largely been conducted outside ESM frameworks [*White et al.*, 2011; *Rosenzweig et al.*, 2014]. While these models may provide highly detailed yield estimates for agricultural decision support, significant challenges remain in marrying spatial scales of their crop growth formulations with those of even the most cutting-edge ESMs.

One challenge lies specifically in the scale at which crop parameters are obtained, as a mismatch between these and ESM resolutions may compromise simulated crop growth and enhance prediction errors [*Baron* *et al*., 2005; *Di Vittorio and Miller*, 2014; *Iizumi et al*., 2014]. Recent studies stress that the representativeness of site-based parameters commonly used in process-based crop models deteriorates at larger scales [*Iizumi et al*., 2014]. When larger-scale parameters are utilized in ESM-crop model formulations, the resulting yields and outputs must be compared against values of a similar scale and bias corrected before interpretation [*Di Vittorio and Miller*, 2014; *Iizumi et al*., 2014]. *Iizumi et al*. [2014] suggest that parameters for major crop growth relationships should be obtained at scales appropriate for simulation, and warn that these could differ substantially from the corresponding site-based parameters due to aggregation. By modifying a number of parameters that related rice yield and growth to regional temperature, the authors showed that those capturing major drivers of regional interannual crop yield variability were likely to display scale dependency. This must be considered for ESM-level simulations, and the authors suggest that cultivar-specific parameters were not appropriate for use in larger-scale simulations [*Iizumi et al*., 2014].

However, even less data-intensive or approximate parameterizations of crop-specific growth may be useful to LSMs if they broadly improve upon unrepresentative, generic formulations adapted from natural PFTs. Though existing ESM crop and agricultural management schemes are still relatively simplistic compared to point-based crop models, incorporating crop-specific growth has in several cases improved basic land surface characteristics related to biogeochemical and water cycling, and energy fluxes. Such inclusions also better represent subgrid heterogeneity, and can reduce biases to enhance model performance for regional climate applications [*Lokupitiya et al*., 2009; *Osborne et al*., 2009; *Levis et al*., 2012; *Liu et al*., 2016]. While many growth parameters may be obtained directly from crop model formulations or from the literature, methods also exist for ascertaining important parameters that have generally required sensitivity testing to fit. Fits based on sensitivity analysis can lead to uncertainty via the parameter ranges used, and can potentially create spurious responses at more extreme environmental conditions.

As an alternative, *Bilionis et al*. [2015] applied a Bayesian approach utilizing a computationally efficient sequential Monte Carlo scheme for soybean growth parameters, highlighting just those parameters that have a significant impact on the crop's development, including carbon-nitrogen allocations at different growth stages, radiation absorption, and specific leaf area. These newly calibrated model simulations displayed improved soy productivity when compared to available sites. Such economical methods of parameter calibration will be important to future ESM crop processes and development, particularly for regions where new crops and agricultural systems are under development (e.g., "climate-smart" systems in Sub-Saharan Africa) or for which literature-published values are varied [*Bilionis et al*., 2015].

As a final consideration, several LSMs separate the soil columns for crop-type PFTs and natural vegetation PFTs, such that they do not interact and/or compete for resources, and in some cases, natural ecosystem dynamics are not operational when crop PFTs are in use [*Levis*, 2010; *Puma and Cook*, 2010; *Levis et al*., 2012; *Li et al*., 2013; *Oleson et al*., 2013; *Pei et al*., 2016]. This simplification may have its limits in capturing the vegetation-climate interactions in multifunctional, heterogeneous, and/or mixed managed/natural agroecosystems, particular as they occur across nonindustrial production systems. However, separating the soil column for cultivation can allow for more efficient implementations of dynamic, climate-responsive management rules, such as the timing and application of irrigation water and nutrients. This can be helpful when trying to isolate and understand the impact of agricultural management, particularly in more uniform, industrial growing regions.

5.2. Coupled and Interactive Climate-Crop Models: Results and Uncertainties

Table 2 shows a summary of the major findings of coupled, dynamic climate-crop modeling studies (detailed below), which provide some of the first investigations of time-varying agricultural impacts. Early work by *Tsvetsinskaya et al*. [2001] integrated key plant growth functions from CERES-Maize process-based crop model [*Jones et al*., 1986], inclusive of cultivar-specific genetic coefficients, with the Biosphere-Atmophsere Transfer Scheme (BATS) [*Dickinson et al*., 1993]. The authors found that the resulting changes in LAI from interactive maize crop response had a statistically significant impact on the surface energy partitioning in dry years (related to large reductions in maize LAI). The authors coupled the modified BATs model to the NCAR RegCM2 [*Giorgi et al*., 1993a, 1993b], and found that the altered surface fluxes during dry years changed temperatures by up to 4°C, and also affected atmospheric moisture, reduced winds (particularly at lower levels), and modified regional rainfall. These experiments were among the first to integrate a dynamic crop component into an ESM, and demonstrate the significant regional climate sensitivity that can result from agricultural modifications to the land surface.

Osborne et al. [2007] developed a coupled climate-crop model using the HadAM3 climate model and the existing MOSES2 LSM [*Lawrence and Slingo*, 2004; *Osborne et al*., 2007], modified to incorporate a crop-specific PFT based upon the growth formulation of the General Large Area Model for annual crops (GLAM) [*Challinor et al*., 2004]. GLAM had been previously used to simulate groundnut, maize, and wheat, and took a "large area" approach on the order of tens to hundreds of kilometers. As such, the model was readily adapted for use with a GCM, and the parameterizations sufficiently generic so as to enable simulation of a range of crops [*Osborne et al*., 2007]. The distribution of the crops across the land surface was ascertained using environmental suitability calculations for each crop, based upon soil moisture, accumulated thermal time, and threshold temperatures. Subsequent study using this coupled climate-crop model to simulate tropical groundnut found that the interannual variations in crop growth had important biogeophysical climate impacts, increasing temperature variability (Figures 5a and 5b), and influencing the mean tropical climate, particularly in more semiarid domains [*Osborne et al*., 2009].

Lokupitiya et al. [2009] developed prognostic phenological models for soybean, maize, and wheat in the Simple Biosphere model (SiB) to quantify the dynamic responses of crop vegetation to climate conditions and the corresponding impacts to water and energy balance. To incorporate these models, crop-specific parameterizations of growth were independently developed to adjust existing SiB prescribed LAI evolution, which were based on remote sensing products. Their crop growth methods account for critical growth stages, processes such as respiration were modified to simulate harvest removals and residue returns, and methods were also included to crudely represent crop rotations. In doing so, the authors found their improved model, SiBcrop, was better able to reproduce the growing season, interannual variability associated with crop rotations and variability in carbon exchanges.

Levis et al. [2012] introduced crop-specific growth into the CLM4cn model [*Lawrence et al*., 2012] by incorporating maize, soybean, and temperate cereals' phenology and carbon allocation algorithms from the Agro-IBIS biosphere model [*Kucharik and Brye*, 2003; *Kucharik and Kucharik*, 2003]. Distributions of the crop PFTs were specified using maps of global crop distributions where the crop coverage area was relegated to the midlatitude regions (Figure 5c). The managed and unmanaged vegetation fractions of the model's grid cells were handled separately (e.g., a separate soil column), without exchanges between the natural and managed vegetation. This improved climate-crop representation produced more realistic crop-specific LAI, and even improved the simulation of summer precipitation over the Midwestern U.S. when compared to observed products (Figure 5d) [*Levis et al*., 2012]. This result was particularly acute when the authors introduced a later planting date for these crops, with significant differences in the simulated climate variables between using earlier and later planting dates. The authors highlighted that accurate representation of the cropping calendars, particularly with respect to planting, is critical to best reproduce observed rainfall and climate conditions [*Levis et al*., 2012].

Most recently, *Liu et al*. [2016] leveraged the framework and photosynthesis model of the WRF/Noah-MP climate-land surface model to incorporate dynamic growth models of maize and soybean in the U.S. Midwest, including key growth stages based upon heat accumulation, respiration rates, carbohydrate allocation, and management (planting/harvest dates). This new Noah-MP-Crop model produced dynamic estimates of maize and soy growth, particularly LAI, which corroborated well with observed data sets, and significantly improved the representation of regional surface heat fluxes, particularly during the early growing season. As Noah-MP-Crop is designed for coupling with WRF, it has widespread potential applications for climate analyses over important agroecological regions. However, this may require that ample data sets are available to calibrate and parameterize the crop model formulation accordingly.

Efforts to integrate across natural and human-managed (agricultural) landscapes have resulted in the conception of modular frameworks in which multiple standalone models of climate, land-surface processes, process-based crop models, and even economic models can be linked. These integrated model frameworks can then be utilized to understand forcings and change across these domains. For example, the BioEarth initiative presents an integrated modeling and assessment framework that utilizes varying degrees of coupling (offline to fully coupled) between atmospheric (climate, chemistry, and meteorology), terrestrial (hydrology,

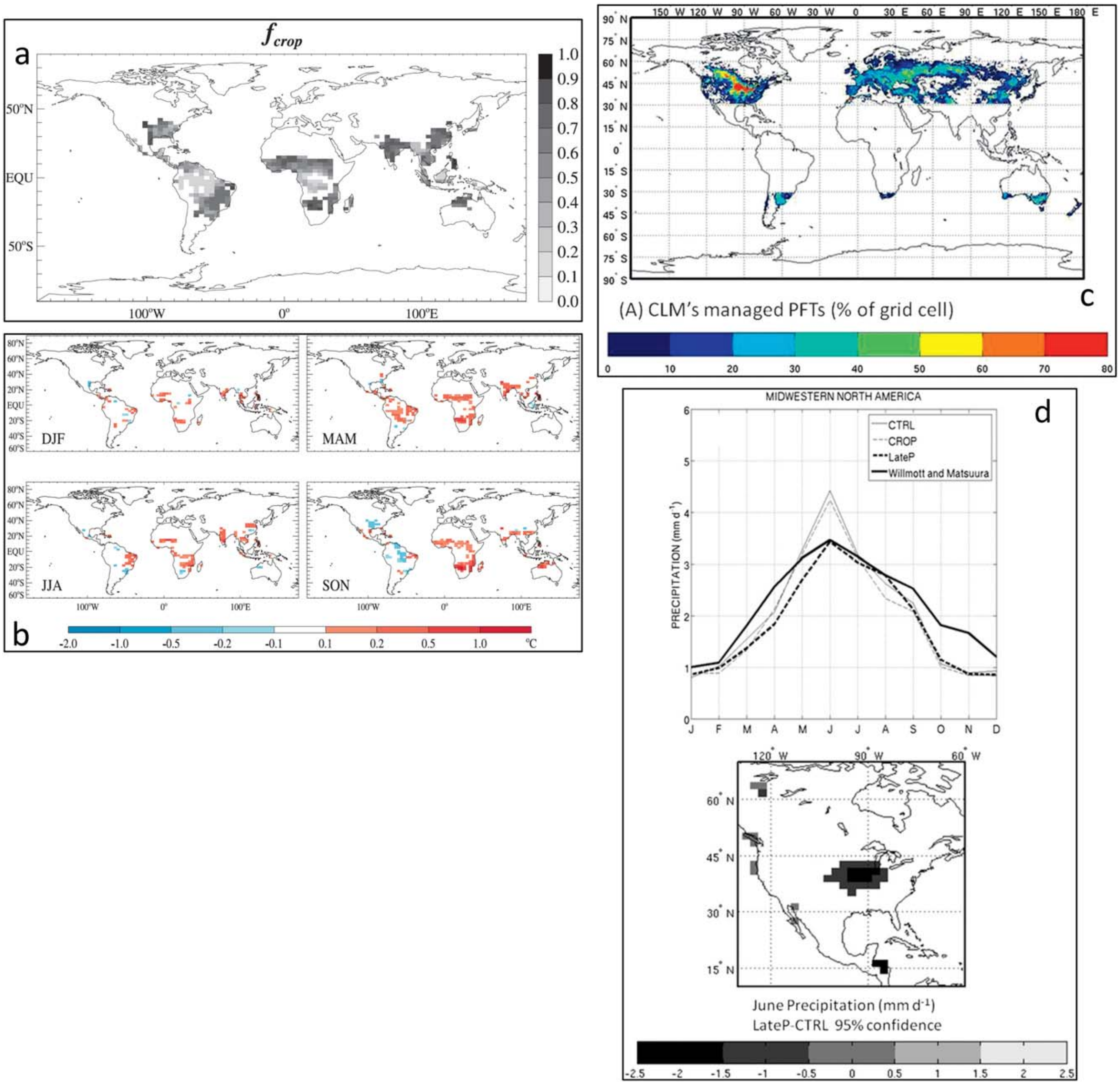

Figure 5. a) Fractional coverage of tropical crops in HadAM3-GLAM coupled climate-crop model. From *Osborne et al.* [2009], Figure 1. b) Difference in the standard deviation of 1.5 m temperatures shown over cropped gridcells and where significant. In many areas, the introduction of dynamic crops increases the temperature variability. From *Osborne et al*. [2009] Figure 8. c) Cropped fractions of the gridcells that contained the introduced crop PFT (maize, soybean and temperate cereals) for the CLM-Crop model. From *Levis et al*. [2012], Figure 1. d) (top) The seasonal cycle of Midwest USA precipitation between model simulations (20 year average) excluding and including crop PFTs, and including crop PFTs in conjunction with a later planting date. The later planting date simulation was the most consistent with observed rainfall (bold dashed line). (bottom) Rainfall differences over the Midwestern USA, shown only for statistically significant gridcells. From *Levis et al*. [2012], Figure 4. Such simulations show the sensitivity of climate simulations not just to the presence of crop PFTs, but also their timing (e.g. planting and phenology).

crop, and ecosystem processes), aquatic, and economic models with an application towards stakeholder decision support at the regional (Pacific Northwest) level [*Adam et al*., 2015]. This project leverages existing models and development activities, along with highly resolved data sets, to evaluate the regional agriculture-climate interactions and feedbacks. BioEarth considers such a structure of coupled models as a variant of earth system models, which are being developed with an emphasis on providing "usable" information for scientists and stakeholders alike. Such integrated models provide a flexible framework that can vary in complexity based upon the main research questions being asked [*Adam et al*., 2015].

These dynamic climate-crop frameworks can potentially be exported and applied to multiple regions and varying domain sizes. However, the quality and resolution of available observed data sets to inform these models may constrain model validation and the types of interactions that can be explored. The end-user should carefully consider what level of coupling is required to answer a given research question (i.e., what is the impact of a particular agricultural management technique on the regional climate system?). Users should also consider if the data availability and fidelity of the model simulation is high enough to warrant reliable results. The development of coupled climate-crop models will be useful for regional integrated assessments or exploring climate-agriculture sensitivities. However, there still exists a need to assess the robustness of climate responses to agricultural management across these modeling frameworks.

6. Representing Agricultural Biogeochemical Cycling and Effects

6.1. Representations of Carbon Storage and Fluxes

Despite outstanding challenges to incorporate agricultural management in ESMs, DGVMs and ecosystem models can enable better representation of carbon cycling, in part due to their incorporation of aboveground and belowground vegetative litter pools. These litter pools decompose at varying rates to emulate the effects of active and passive carbon stores, and emissions to the atmosphere [*Bonan et al*., 2003; *Sitch et al*., 2003; *Krinner et al*., 2005; *Davidson and Janssens*, 2006]. A benefit of incorporating crop-specific or crop-type PFTs into such a framework is that it allows for dynamic simulation of their growth, carbon uptake, and assimilation. These frameworks also include crop contributions to modeled litter pools and their subsequent decomposition based upon the crop-litter quality (which may consider lignin content, polyphenols, C:N ratios) and quantity, agricultural management (e.g., feeding stover to animals, tillage, and residue incorporation), and climate conditions. Studies show that such DGVM/ESM frameworks improve simulated atmospheric CO_2 cycles at various latitudes, measurements of soil carbon stocks, surface-atmosphere energy and moisture fluxes, and net primary productivity in different biomes/regions [*Bonan et al*., 2003; *Sitch et al*., 2003; *Krinner et al*., 2005; *Davidson and Janssens*, 2006]. Further development and differentiation of crop-type PFTs allow for more comprehensive assessments of biogeochemical feedbacks between crop growth, management, and climate processes, and could eventually allow researchers to assess the potential for agricultural soil carbon sequestration.

As the ambitious Paris Climate Agreement now enters force, momentum has been building for a global initiative to build soil carbon stocks by 0.4% per year over a 25 year period [*Koch et al*., 2015; *Averett*, 2016], in large part leveraging carbon-management of agricultural soils. However, there exists a relative paucity of data sets to evaluate the potential of this soil carbon accumulation rate to be realized across larger spatial scales. The current body of existing site-based assessments, while growing, yield a wide range of results that are very dependent on local conditions [*Palm et al*., 2014; *Powlson et al*., 2014]. It has additionally been suggested that heterogenous calculation methods, terminology, and definitions for land-use emissions and biogeochemical exchanges, and the lack of standardization across these, also accounts for much uncertainty [*Pongratz et al*., 2014]. However, the outstanding uncertainties in agricultural soil carbon sequestration and atmospheric exchanges provides an entry point for ESM development and sensitivity testing across soil conditions and management practices. This is particularly salient as climatologists seek to better quantify land-use GHG emissions and leverage agriculture as a mitigation tool.

There has been much initial work to characterize the role agriculture plays in modulating and/or amplifying soil carbon fluxes. *Drewniak et al*. [2013, 2015] leveraged the CLM-CN—with a fully coupled carbon-nitrogen cycle—to quantify the impact of crop residue management and nitrogenous fertilizers on soil carbon storage and seasonal carbon fluxes. The authors also improved upon the above-described CLM crop formulation for maize, soy, and wheat [i.e., *Levis et al*., 2012]. Comparisons of this new CLM-Crop model with monitoring and observational products showed improved gross primary productivity for intensively cropped regions. For soybean in particular, there was good agreement in the representation of seasonal carbon fluxes (Figure 6a) [*Drewniak et al*., 2013]. In addition, the authors showed the large quantities of residue return were required to slow the decline in soil carbon stocks (Figure 6b), recovering some of what is lost through conversions from natural vegetation [*Drewniak et al*., 2015]. In addition, the inclusion of nitrogenous fertilizers was found to be a limiting factor in the amount of carbon stored [*Drewniak et al*., 2015]. The authors also noted that any simulated soil disturbance due to cultivation will decrease soil carbon content,

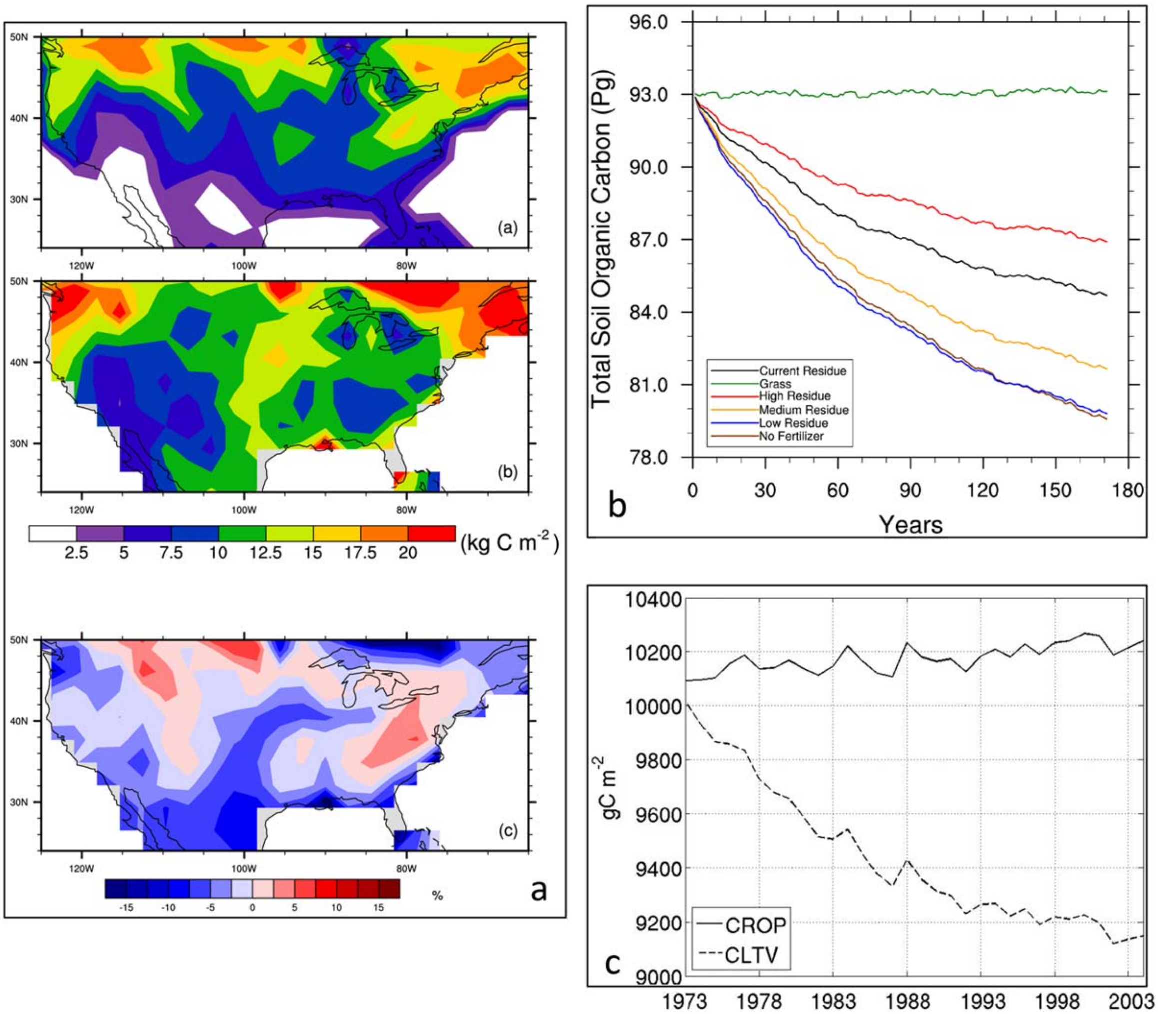

Figure 6. (a; top) Simulated soil organic carbon by CLM-Crop, (middle) IGBP soil organic carbon, (bottom) the difference between the CLM-Crop and IGBP soil carbon, with most grid cells showing less than a 5% difference. From *Drewniak et al*. [2015], Figure 1. (b) The change in simulated soil organic carbon at varying levels of residue return and nitrogen management, with the least carbon loss occurring at the highest levels of return. From *Drewniak et al*. [2015], Figure 6. (c) Soil organic carbon simulated for the central United States under a transition from natural vegetation to crops (bold black line), and then under cultivation (soil disturbance due to tillage and plowing). The act of cultivation leads to large decreases in soil carbon stores, where just including cropped areas did not display such sensitivity. From *Levis et al*. [2014], Figure 2.

though how much is dependent on management practices. Such findings are consistent with observed assessments and comparisons of management practices to date: the total amount of residue and its quality largely limit soil carbon sequestration potential [*Palm et al*., 2014]. Indeed, agricultural inputs—fertilizer, soil amendments, and residues—are necessary considerations for quantifying soil carbon accumulation rates and fluxes in modeled environments.

In addition, cultivation practices which may disturb and overturn the soil, in the form of tillage and ploughing, are equally important to estimating soil carbon storage and fluxes over time and space. *Levis et al*. [2014] performed simulations with the biogeochemically interactive version of the CLM4.5 (CLM4.5bgc) [*Koven et al*., 2013; *Oleson et al*., 2013] which introduced land-use conversion to agricultural crops and incorporated the direct effects of cultivation (i.e., tillage and ploughing) on soil carbon decomposition. The authors introduced the effects of cultivation via a set of enhanced decomposition factors for litter and soil carbon pools. Overall, their simulations resulted in decreased soil carbon stores particularly in the United States (Figure 6c). Furthermore, simulations that lacked the inclusion of cultivation substantially underestimated land-based CO_2 emissions [*Levis et al*., 2014]. These findings are generally consistent with those of *Drewniak et al*. [2015] using a more recent CLM version, in that the models robustly simulate a loss of soil carbon due to soil disturbance and cultivation. These effects are particularly acute on U.S. soils, while globally, the type of management practice is important for curbing losses. Interestingly, *Levis et al*. [2014] also found that modeling crops alone, without cultivation, actually enhanced soil carbon storage—a finding the authors expressed as unexpected given the 19th and 20th century declining trends. However, recent findings show agricultural crops' propensity to significantly modulate seasonal atmospheric CO_2 [*Gray et al*., 2014; *Zeng et al*., 2014b], suggesting that domesticated plants have distinctive growth responses compared to colocated natural species. These studies provide an even stronger argument for the need to treat crops and agricultural vegetation as distinct from natural PFTs or prescribed vegetation types, particularly in terms of their nutrient allocation, growth, and other biophysical/chemical processes.

It is important to note here, however, that ESM-based global soil carbon assessments do not preclude, and are not a substitute for, site-based assessments. This is particularly true in regions where there is a paucity of management data. Rather, ESM analyses of soil carbon provide a framework for understanding the potential soil carbon fluxes given basic boundary information. ESMs can also test a range of regionally suitable carbon management options, and motivate site-based data collection where the resulting modeled agricultural soil fluxes are highly variable. However, it is possible that economic incentives and pressures may be bigger constraints on agricultural soil carbon storage than the regional biophysical limits [*Grace et al*., 2012].

6.2. Representations of Soil Properties to Better Quantify Agricultural Impacts

To facilitate better representations of biogeochemical cycling, it is critical that ESM land surface components capture important soil types, attributes, and their distributions, insofar as they are pertinent to the agricultural systems they host. Thus, the development of ESM soil representation is a parallel endeavor to representing aboveground crops and management, particularly when trying to assess the ability of agriculturally managed soils to uptake carbon [*Paustian et al*., 2016]. Under warmer climate conditions, "fast" decomposing belowground organic matter may be susceptible to even faster decomposition rates [*Van Groenigen et al*., 2014]. This could make building carbon stocks to sequester carbon, and mitigate climate change, more challenging. However, if decomposition rates slow, or occur more slowly than the buildup of litter or biomass, then carbon removals become more viable. The exact sensitivity of these decomposition processes to climate change, particularly by way of temperature and moisture regimes, is still under investigation [*Davidson and Janssens*, 2006; *Todd-Brown et al*., 2013], and could be an entry point for analysis using ESMs with improved soil representation and response to climate processes.

Lawrence and Slater [2008] comment that most GCMs model soil properties by using parameterizations based on mineral soils and soil texture, rather than representing organic soils and material. To remedy this, they utilized a global data set of soil carbon content from the International Global Geosphere-Biosphere Program's *Global Soil Data Task* [2014] to develop parameterizations of thermal and hydraulic properties based upon organic soils [*Lawrence and Slater*, 2008]. When incorporated, these soils retained cooler temperatures and more moisture, though not saturated at the surface, which limited soil evaporation. This had the effect of reducing the low cloud fraction and warming summer air temperatures, improving overall model simulations. While this development is targeted toward peatlands and permafrost areas, this may have relevance to discussions for increasing soil carbon stocks to mitigate against ongoing and future climate change.

The role of soil microbiology is also of prime importance to agricultural management and biogeochemical cycling, particularly for low input systems. *Wieder et al*. [2013] incorporated microbial processes explicitly into the CLM4cn by developing microbial biomass pools within a soil biogeochemistry module. This capacity directly simulated mineralization processes and responding to changing climatic/environmental conditions. The incorporation of the microbial model enabled a dramatic increase in the model-explained spatial variation in soil carbon observations [*Wieder et al*., 2013]. This is in contrast to more traditional methods of implicitly simulating decomposition through microbial processes. Ultimately, this development allowed for better estimation of soil carbon under both changing climate conditions, and, potentially, variations in regional management of agricultural litter/residue.

It has also been noted that a substantial amount of plant-produced photosynthate is utilized for acquiring nutrients via symbiotic funghal and microbial relationships [*Kaiser et al*., 2015; *Shi et al*., 2016]. Not accounting for these transactions may hamper estimates of biospheric carbon uptake [*Fisher et al*., 2010; *Shi et al*., 2016]. Improved models of plant nutrient uptake in this regard have potential to integrate with ESM/LSM agricultural representations, enabling better simulations of agricultural carbon cycling. For example, *Shi et al*. [2016] recently coupled the Fixation and Uptake of Nitrogen (FUN) model [*Fisher et al*., 2010], which accounts for biogeochemical interactions with mycorrhizal roots, N-fixing microbes, and retranslocation, to the CLM 4.0. The resulting simulations indicated a downregulation in global net primary production [*Shi et al*., 2016]. Representing more comprehensive plant nitrogen-carbon interactions in ESM land surfaces is particularly important as we move toward regional agricultural systems that build soil fertility and increasingly consider organic production methods.

6.3. Including Agricultural Nitrogen Fertilizer Applications

A full representation of agricultural systems cannot be complete without representation of the nitrogen cycle, accommodating for both low input and high intensity systems. *Jain et al*. [2013a, 2013b] utilized the ISAM C-N model to resolve both carbon and nitrogen fluxes between vegetation, soil, and the atmosphere, as well as the below ground litter pools and soil organic matter. In studying historical land-use transitions from 1765 to the late 2000s, the authors found that explicit N-cycling increased net terrestrial carbon emissions. They suggest that to most accurately capture GHG exchanges between the land surface and the climate system, dynamic nitrogen cycling could be a limiting factor and must be resolved [*Jain et al*., 2013a]. This is particularly important to consider as agriculture attempts to reach carbon neutrality or serve as a net sink of anthropogenic carbon. The role of nitrogen overuse or nitrogen (N) limitation (given the region and farming system) must be examined at varying scales [*Davidson and Kanter*, 2014; *Kanter et al*., 2016]. Nitrogen dynamics can be a limiting factor for carbon cycling, with high-input agricultural systems that rely on nitrogen fertilizers experiencing larger gains in overall biomass. Efficient agricultural nitrogen cycling and uptake is also imperative to take advantage of potential CO_2 fertilization effects. However, nitrogen cycling processes are also subject to changes under changing environmental conditions and could prove to be a prime limiting factor in agricultural management for mitigation [*Stocker et al*., 2013a].

In general, ESMs are increasingly incorporating and improving nitrogen cycle representations, which will further aid in quantifying the agricultural nitrogen forcing entering the natural system. Some ESMs can now explicitly represent: mineralization, fixation, root uptake, atmospheric deposition, as well as denitrification and nitrogen leaching processes, along with the variety of nitrogen pools and interpool fluxes and transformations [*Dickinson et al*., 2002; *Thornton et al*., 2007; *Thornton*, 2009; *Gerber et al*., 2010; *Zaehle and Friend*, 2010; *Dunne et al*., 2013; *Hurrell et al*., 2013; *Smith et al*., 2014b]. A comprehensive review of the nitrogen cycle features of various models can be found in *Zaehle and Dalmonech* [2011]. Many of the studies incorporating N-cycle components suggest that carbon-cycle-only representations may overestimate the potential for biospheric sequestration of atmospheric carbon under climate change conditions [*Zaehle and Dalmonech*, 2011; *Smith et al*., 2014a]. *Dickinson et al*. [2002] further explored the biogeophysical effects of explicit nitrogen cycling, by focusing on how its inclusion controlled evapotranspiration. In their model, nitrogen stores and exchanges between pools were sensitive to climatic variables such as rainfall and temperature, which further affected aspects of plant growth, such as LAI [*Dickinson et al*., 2002]. Such considerations are important for determining the efficacy of proposed climate change "benefits" to agriculture, such as CO_2 fertilization, which stands to be limited by nitrogen cycling interactions [*Reich and Hobbie*, 2012; *Reich et al*., 2014]. These effects are currently subject to large uncertainties and, potentially, overprediction in ESMs that participated in the Fifth Coupled Model Intercomparison Project (CMIP5) [*Thornton et al*., 2007; *Smith et al*., 2015].

ESMs' N-cycling implementations must also be adapted to consider nitrogen "inputs" in the form of agricultural nutrient applications, mineral and organic, uptake and losses—particularly the agricultural nitrogen "forcing" spurred by the advent of the Haber-Bosch process [*Erisman et al*., 2008; *Galloway et al*., 2008]. The term forcing is used here as modern agricultural N inputs diverge substantially from the natural boundaries and cycling [*Rockström et al*., 2009], and usually require and follow a prescribed schedule. This ranges from increasing precision applications in highly productive areas to large variability (in both amount and timing) across low-productivity zones. Acquiring reliable information about the timing and amount of nitrogen inputs can be challenging, although this can be better constrained in areas that use the most mineral fertilizer. One solution for ESMs is to prescribe a seasonal application schedule that broadly follows the amounts obtained via available data sets [*Potter et al*., 2010; *Mueller et al*., 2012b], timed as a function of important stages in a crop's growth cycle. For example, the CLM4.5 has the option of utilizing crop-specific application amounts (obtained from USDA national fertilizer statistics). These fertilizer inputs are specified at a constant rate for a 20-day period beginning at emergence, in which the mineral fertilizer is added directly the soil mineral nitrogen pool [*Drewniak et al*., 2013]. The model is then able to capture coupled carbon-nitrogen dynamics, which can be useful in assessing the ultimate carbon fluxes (as a result of simulated crop growth and biomass accumulation) described above.

These efforts are an important initial step to including the effects of agricultural management in ESMs, particularly with respect to nutrient and organic matter input (including residues). Continued developments in this vein will better constrain the role of management in agroecosystem carbon sequestration for both improved soil health and climate change mitigation.

7. Coordinating Agriculture-Climate Assessments and Existing Data Constraints

7.1. Coordinated Assessments of Agriculture and Climate Systems

As ESMs develop better representations of agriculture, there is a need to assess the consistency or divergence in their climate responses, particularly in relation to future development trajectories. Additionally, ESMs may be applied to broadly assess which management practices constitute regional "sustainable intensification" and contribute to potential GHG mitigation under climate change conditions. To this end, coordinated assessments and model intercomparisons provide a mechanism to both evaluate these improved model capabilities, and bracket the range of potential responses to future scenarios of LULCC.

There exist several efforts to coordinate ESM-based assessments of LULCC impacts more broadly, incorporating both natural and anthropogenic drivers. Agricultural management will inevitably be among the dominant land-use forcings during the historical period, driven largely by demand, new settlements, and population growth. *Cramer et al*. [2001] was among the first formative intercomparisons of early dynamic vegetation models to assess the impacts of anthropogenic GHG forcing on natural terrestrial ecosystems, particularly by way of carbon cycling. CO_2 forcing trajectories associated with the early Intergovernmental Panel on Climate Change (IPCC) IS92a emission scenarios [*Houghton et al*., 2001] were used to drive one GCM, from which the climate response was then taken as inputs to six dynamic vegetation models. The six models showed a wide range of terrestrial carbon uptake, although most models agreed that the terrestrial biosphere was reduced in this capacity as the simulation progressed through 21st century projected conditions. This was in part influenced by strong responses in tropical biomes [*Cramer et al*., 2001]. The authors suggest that the variability in magnitude and spatial patterns of carbon uptake of these natural systems warrant further investigation. This point is particularly salient for ESM development efforts, because agricultural management stands to further modify the landscape level carbon uptake potential from natural ecosystems. These changes must be further evaluated in the context of a changing climate. A new generation of coupled climate-ecosystem models inclusive of agriculture may provide improved estimates for modified carbon cycling under both land and GHG anthropogenic forcings. Table 2, "Coordinated Assessments," summarizes the climate responses of two major model intercomparisons to date (detailed below), which include significant agricultural land conversion contributions.

One of the first major model intercomparisons to systematically assess the impacts of LULCC on regional and global climates using a common set of simulations was the Land-Use and Climate, Identification of Robust Impacts (LUCID) [*Pitman et al*., 2009; *Boisier et al*., 2012; *De Noblet-Ducoudré et al*., 2012]. These simulations compared the land cover and vegetation changes between 1870 and 1992, with all other forcings set to modern conditions [*Pitman et al*., 2009]. Each model group implemented these land cover changes in ways that were compatible with their respective land surface modeling components, and no coupled or dynamic global climate-crop models were used. Such model-specific implementation enabled an efficient intercomparison targeted toward the IPCC Fifth Assessment Report [*Stocker et al*., 2013b]. Furthermore, attempts to harmonize over a particular land simulation approach would have potentially required model retuning or more substantial, time-consuming development efforts [*Pitman et al*., 2009]. LUCID's intercomparison revealed some important points of agreement and divergence among the modeled responses, and gave an initial indication of regional variability in climate response (detailed in section 3 above). However, these disparate implementations did also introduce a source of uncertainty among the models' results [*Pitman et al*., 2009; *De Noblet-Ducoudré et al*., 2012]. Additionally, land cover changes that occurred between the time periods also included changes in natural ecosystems and nonagricultural land conversions. This complicates assessments of the agricultural contribution to the documented changes (though agriculture may have directly and indirectly dominated historical land-use transitions). However, this intercomparison was important in highlighting a previously underdeveloped component in climate models—land surface change, particularly by way of agricultural conversions. LUCID underscored the importance of developing better methods and best practices of ESM land surface representation and intercomparison.

More recently, *Brovkin et al*. [2013] conducted a model intercomparison between six CMIP5 ESMs and compared their biogeophysical responses to specified LULCC forcing under the lowest and highest Representative Concentration Pathways (RCPs), RCP2.6 and RCP8.5, respectively. Accompanying these two RCPs are harmonized historical and future LULCC trajectories adapted from Integrated Assessment Modeling (IAM) efforts, which have integrated models of land and resource use with models of global socioeconomic development in a coordinated framework [*Van Asselen and Verburg*, 2013; *Meiyappan et al*., 2014; *Collins et al*., 2015a]. To utilize these trajectories in ESMs, they had to be adapted and converted using the Global Land-Use Model, which includes transitions between natural vegetation, crops and pasture, urban areas, and secondary growth [*Hurtt et al*., 2011]. These land transition scenarios show increases in cultivated lands and continued conversion from natural ecosystems (e.g., deforestation) under RCP8.5. Under RCP2.6 conditions, an increased reliance on biofuels and bioenergy drives more moderate increases land-use and land cover.

Similar to the LUCID studies described above, one prime source of uncertainty in this assessment are the unique implementations of LULCC specifications and transitions following the harmonized scenarios, partially owing to the ways in which each model classified land-use and vegetation types [*Brovkin et al*., 2013]. The models included span the range of approaches discussed within this review: from prescribed, idealized land cover classes to crop-specific PFTs (though explicitly coupled climate-crop models were not utilized). Assessing how well ESMs with crop-specific PFTs represent observed carbon exchanges and stocks proves challenging, however. This is partly due to outstanding limitations in the availability of spatial and temporal global data sets that can be used for model evaluation. On the other hand, ESMs that represent crops as generic grasses do not explicitly resolve important biogeochemical effects, such as exchanges between carbon pools. This may have important ramifications for land cover transitions (such as transitions between native forest, pasture, and intensive cropping systems) and their impact on climate change [*Brovkin et al*., 2013].

Overall, *Brovkin et al*. [2013] show that while the global climate effects of GHG emissions exceed the LULCC forcing across the ESMs, the latter becomes regionally significant when changes exceed 10% of the area. In particular, for larger LULCC areas, there were statistically significant changes in albedo and partitioning between latent and sensible fluxes, which would contribute to the significant changes in surface air temperature found. For these reasons, the agricultural community requested that temperature and moisture variables from the agricultural fraction of grid boxes be included as output to capture the differential impact of climate change on agricultural lands [*Ruane et al*., 2016]. The authors also found that the LULCC became more important as a forcing under the RCP2.6 scenario [*Brovkin et al*., 2013], as the radiative forcing due to GHG emissions stabilize.

The most recent LULCC intercomparisons, such as the CMIP6 [*Eyring et al*., 2015] endorsed Land-use Model Intercomparison Project (LUMIP) [*Lawrence et al*., 2016a], are important to ESM agricultural representations for the following reasons:

1. They allow for systematic assessment of the most important research questions relating agricultural land-use and management to regional and global biogeophysical and biogeochemical climate processes. While individual, region-specific, or model-specific studies can highlight important interactions and their scales of influence, multimodel assessments are critical to assess the robustness and uncertainties of these agricultural impacts on climate and ecosystems across both time and space, and in the presence of other forcings.
2. Model intercomparison efforts, such as the CMIP5 land-use harmonization activities [*Hurtt et al*., 2011], will be instrumental in identifying those agricultural components, parameterizations, and representations that show the most agreement and/or divergence in climate response. Additionally, ESMs' relatively coarse resolution is still an outstanding limitation for agricultural representations. However, intercomparisons across diverse, continually advancing ESMs present an opportunity to assess the effect of resolution and complexity in simulating key climate-agriculture interactions. In doing so, these efforts can identify model biases and needs for model improvement that will help frame near-future ESM developmental priorities and inform data collection efforts.

3. In addition, coordinated studies can help modeling groups leverage the needed resources and expertise for development. For example, efforts to harmonize over land-use distributions, trajectories, and management led to the development of the HYDE 3.1 database. HYDE 3.1 synthesized this LULCC information and made it accessible to the greater ESM community [*Klein Goldewijk et al*., 2011a]. HYDE 3.2 further develops the data sets and methods detailed in *Klein Goldewijk et al*. [2011b], *Hurtt et al*. [2011], and *Brovkin et al*. [2013]. Along with the second Land-use Harmonization project (LUH2), HYDE 3.2 now provides ESM groups with harmonization protocols, data sets, and inputs for CMIP6-supported studies (e.g., LUMIP) [*Lawrence et al*., 2016a]. The provisioning and support of these data sets will enable coordinated model intercomparisons to more systematically consider complex climate interactions, particularly in rapidly developing agricultural regions.

7.2. Data Availability, Constraints, and Needs

To realize the full utility of these model intercomparisons, and contextualize their findings and implications, more comprehensive agricultural data sets are required. These must include spatial and temporal information on crop coverage, phenology, and management conditions. Such data sets are vital to improved ESM representations of agriculture and their validation of simulated agro-climatic interactions. However, there has been a relative paucity of reliable production and management data sets for ESM development. Many of those available—such as through the UN Food and Agriculture Organizations Statistics Database—rely on government reported production and management information. These data are generally spatially aggregated and thus eliminate needed information on spatial heterogeneity. Even in countries with relatively advanced data collection, survey methods, and large areas of high productivity, inconsistencies in reported statistics and other data sets make model validation and process evaluation challenging [*Nazemi and Wheater*, 2015a, 2015b; *Khan et al*., 2016]. This leads to significant differences between modeled and data-based estimates of relevant climate variables, agricultural water use, and production, particularly when local crop coverage and management conditions are highly dependent on climate conditions [*Leng et al*., 2013; *Nazemi and Wheater*, 2015a]. As such, while there is still utility in leveraging new and evolving data sets that speak to global and regional agricultural coverage and management, there is also a need to to be wary and cognizant of their deficiencies and potential uncertainties.

With these caveats in mind, several data sets and techniques are available and/or under development that provide high-resolution (ranging from 5 min to 0.5°) modern global average crop coverage, planting and harvest dates, irrigation, and nitrogen applications, and ranges of interannual variability [*Monfreda et al*., 2008; *Ramankutty et al*., 2008; *Portmann et al*., 2010; *Sacks et al*., 2010; *Mueller et al*., 2012a; *Siebert et al*., 2014; *Wada et al*., 2014]. Many of these data sets, such as crop coverage and planting dates, are specific to present-day distributions of agriculture. Some data sets for irrigation, on the other hand, merge global irrigated areas data with model estimates that can be extrapolated to time-varying irrigation rates. Such data sets can currently provide only a modern average or, in some cases, a "snapshot," of global agricultural extent and management. However, their inclusion can better inform and improve modern day ESM climate simulations, evidenced by the studies reviewed herein. This body of work illustrates that omitted agricultural processes may be a potential source of model land surface biases.

In addition, efforts toward improved remote sensing techniques for establishing crop phenology and productivity can further inform model development and contribute to benchmarking efforts [*Galford et al*., 2008; *Jain et al*., 2013b; *Mondal et al*., 2014a; *Lobell et al*., 2015; *Khan et al*., 2016]. For example, *Galford et al*. [2008] undertook a wavelet analysis on a timeseries MODIS Enhanced Vegetation Indices (EVI) to estimate overtime increases in land conversion to row crops in Mato Grosso, Brazil—an area of both rapidly expanding agricultural production and at-risk natural ecosystems. Advances have also been made using remote sensing products to determine cropped areas, intensity, and even particular crop species in regional agroecosystems. *Mondal et al*. [2014a, 2014b] leveraged MODIS EVI from 2000 to 2012 to determine phenological peaks in wheat and chickpea-based systems in central India. The authors found that both crops displayed a strong sensitivity to wintertime daytime temperature and monsoon onset [*Mondal et al*., 2014a, 2014b]. *Khan et al*. [2016] merged multiple high-resolution Landsat data sets to ascertain the within-growing season areas under wheat cultivation for the Punjab region, Pakistan. This region constitutes Pakistan's bread basket and is subject to high degree of climate variability. Such in-season crop mapping can inform the actual spatial area devoted to high-input crops and is useful to high-resolution, time-varying climate simulations.

Indeed, the variety of remote-sensing techniques for obtaining cropping system data—spatial coverage and variability—are useful for a range of applications. *Jain et al*. [2013a, 2013b] compared four different methods using both MODIS and Landsat-derived indices for mapping cropping intensity. While the Landsat methods provided the most accurate estimates, they were constrained by much smaller scales of analysis. In contrast, a more recently available technique, a MODIS hierarchical training method, can also reliably quantify the intensity of cropping systems, or heterogeneity such as intercropping or mixed plots. It can furthermore be applied over larger areas, making this technique potentially highly relevant for ESM applications [*Jain et al*., 2013b].

In a more global context, the G-20 mandated Group on Earth Observation's Global Agricultural Monitoring Community (GEOGLAM) is a coordinated effort to monitor, collect, and make agricultural data for both crop and pasture available at multiple spatial and temporal scales [*Whitcraft et al*., 2015]. This data collection effort coordinates across multiple remote sensing products to provide a range of resolutions for agricultural variables, including: crop mask and coverage, type, crop condition indicators, yield and biophysical variables, environmental variables pertinent to crop growth, and management [*Whitcraft et al*., 2015]. Such information will be valuable for future ESM/LSM boundary and initial conditions, benchmarking, and validation, and thereby potentially improve regional climate simulations.

There also exist few quality data sets related to key land surface-climate processes and variables. However, these data are required to gain a full understanding of how agriculture may impact regional environments. For example, understanding the impacts of agriculture on surface energy partitioning and moisture fluxes demand time-varying, and highly resolved data (e.g., turbulent fluxes and soil moisture). To this end, *Seneviratne et al*. [2010] provide a comprehensive review on the availability and progress in creating widespread soil moisture data sets. Progress has indeed been made on remote sensing products, for example the Gravity Recovery and Climate Experiment (GRACE) [*Tapley et al*., 2004] for a wide array of water resource applications and newer missions such as the Soil Moisture Active Passive (SMAP) [*Entekhabi et al*., 2010]. However, there are still major gaps in direct and reliable ground-based measurements, which can be highly resource intensive to collect [*Seneviratne et al*., 2010; *Pokhrel et al*., 2016]. Likewise, eddy-covariance estimates of turbulent fluxes, such as those obtained through FLUXNET sites [*Baldocchi et al*., 2001], have been of great utility in the site-based validation of LSMs.

Yet, larger-scale estimates and a more coordinated network of flux sites are required for better ESM-observation comparisons. ET estimates based on mixed methods merging flux towers, remote sensing products, such as MODIS, and modeled water and energy balance, can be useful point of comparison for ESMs [*Mu et al*., 2007; *Jung et al*., 2009]. For example, *Jung et al*. [2010] established a data-driven, machine learning technique merging point-wise FLUXNET ET estimates with other ground observations and remote sensing data to create a global data set of land ET [*Jung et al*., 2009, 2010]. Using this product, the authors identified recent global declines in land ET driven largely by soil moisture limitations in Africa and Australia [*Jung et al*., 2010]. Such findings may be important to constraining hydrological change in those regional agroecosystems. However, these data sets may show uncertainties and inconsistencies with observed sites and/or in their long-term trends [*Seneviratne et al*., 2010, detailed in Table 2]. These deficiencies must be identified and rectified prior to these data sets' use as ESM validation and process understanding tools.

Last, there are also information deficiencies on the impacts of LULCC on soil carbon stocks, and methodological discrepancies in their measurement and quantification. This makes establishing baselines for soil carbon accumulation challenging [*Pongratz et al*., 2014; *Scharlemann et al*., 2014; *Bradford et al*., 2016]. As such, there is a need for constructing extensive, high-quality monitoring efforts that allow for ground truthing of remote-sensing-based estimates. When used together, these observations can lend themselves to improved ESM simulations and provide needed insight into the mechanisms by which agriculture impacts environmental and climate systems.

8. Key Questions for Climate-Agriculture Interactions and Next Steps for Continued Work

The preceding sections provide a general review of ESMs' emerging capacities to represent agriculture and management in their land surfaces. Table 2 summarizes the methods and resulting climates interactions for the studies summarized herein. Below, we identify several key research questions and potential lines of future inquiry and model development, emphasizing the role of coordinated efforts.

8.1. What Are the Immediate Needs and Areas for Near-Term Development?

The studies reviewed herein have generally revealed many sources of uncertainty in accurately quantifying agriculture-climate interactions. However, there is convergence around a few key simulated responses. Conversions from grasses to more intensified agricultural systems in temperate regions generally lead to enhanced latent heat fluxes and reduced temperatures at the height of the growing season. This response is particularly significant when irrigation is introduced. Additionally, irrigation is a strong climate forcing in high-production, water-limited regimes, and can interact surface climate processes and even synoptic-scale circulation features. Thus, future ESM development work should focus on improving the representation, amount and variability, of irrigation, and include this in the suite of anthropogenic climate forcings [*Cook et al*., 2014].

Furthermore, agricultural residue, crop-nutrient interactions, and soil management critically alter natural biogeochemical cycles. Current agricultural biogeochemical impacts include pollution ranging from GHG emissions to coastal aquatic dead zones [*Zhang et al*., 2015]. The experiments discussed herein show that agricultural soil management, such tillage and residue return, can impact soil carbon stocks. Conventional management techniques, such as high levels of tillage, reduce soil carbon (and enhance carbon emissions), which can facilitate erosion over time [*Montgomery*, 2017]. Thus, it is important to further develop ESM biogeochemical cycling components and soils representation to incorporate these agricultural management forcings and their long-term impacts. This is additionally important given the newly placed emphasis on leveraging agricultural soils to sequester anthropogenic carbon, which may require sustained management techniques (e.g., no-till) [*Montgomery*, 2017]. Model development in these respects will greatly benefit from rigorous benchmarking evaluation efforts and model intercomparisons that bracket the range of simulated climate response to these forcings. Such assessments are also critical to identifying the most important regional agricultural "forcing" components.

8.2. How Can We Better Quantify and Understand the Influence of Agricultural Management on Regional Climate Processes?

The studies summarized above illustrate how agricultural land cover and use can modify regional moisture fluxes, energy balance, and even interact with synoptic-scale circulation features. However, model intercomparisons show that varied implementation of agricultural land cover and management in ESMs lead to disparate model results, which make ascertaining and understanding robust physical responses difficult [*Pitman et al*., 2009; *Boisier et al*., 2012; *De Noblet-Ducoudré et al*., 2012; *Brovkin et al*., 2013]. A better understanding and representation of these agriculture-climate interactions can improve regional and global climate simulations. Additionally, improved representations allow more investigation of how agriculture may amplify or detract from anthropogenic GHG forcing.

An important secondary question can also be posed: to what level of detail must agricultural management be represented to capture the most robust and influential climate feedbacks and responses? The inclusion of process-based crop models and/or dynamic crop functional types demands a higher level of input information and detail. These can include soil conditions, crop-specific growth and/or genetic traits, and management options, such as the level of tillage and the timing and amount of irrigation and fertilizer applied in response to crop growth. As mentioned in section 7.1, while data collection is ongoing, there are few existing global and regional data sets for these agroecosystem attributes that can aid in rigorous model benchmarking.

In this regard, coordinated benchmarking initiatives for land surface model performance will be critical to the evaluation of agricultural processes in ESMs. In particular, the recent International Land Model Benchmarking Project (iLAMB) [*Luo et al*., 2012] is currently undertaking a comprehensive land surface model-data comparison in order to elucidate key processes in simulating climate-terrestrial ecosystem interactions. iLAMB will define and create benchmarks and model evaluation metrics and criteria, and identify areas of robust model agreement and outstanding deficiencies. *Luo et al*. [2012] provide a detailed discussion of the state of available data for model validation and development, including surface turbulent fluxes and energy balance, respiration and productivity, and impacts to biogeochemical cycling. The authors also detail techniques and approaches to devising iLAMB measures useful for improving the representation of historical and current terrestrial natural ecosystems, their influence on the climate system, and projected future changes.

The studies reviewed herein show that 20th century agriculture has had significant impacts on global biogeochemical and water cycling. These impacts stem from land cover change, management choices, and even the growth attributes of modern, improved crop varieties [e.g., *Gray et al*., 2014; *Zeng et al*., 2014b]. Thus, given the centrality of global agriculture as a land surface forcing, we suggest that the iLAMB efforts should include an explicit subfocus on how agricultural representations might improve model performance against critical benchmarking products and measures. In order to address this, however, the data sources used for benchmarking and model comparison must adequately reflect time-varying agricultural land management, including crop growth and phenology, irrigation and nutrient applications, tillage, and other cultivation practices. In this respect, land surface benchmarking efforts could leverage the data collection underway from initiatives such as GEOGLAM [*Whitcraft et al*., 2015].

To better constrain model development and uncertainty in these respects, we must address the important question: at what scale are our questions of agriculture-climate interactions being posed, and are the necessary data available? There is potential scope to generalize over input information for more homogenous growing regions, such as industrialized monocultures, where management can be relatively more uniform. However, resolving cropping and management differences, and acquiring the necessary input data, for highly heterogeneous systems—many of which lie in highly variable climate regimes (such as the semiarid tropics)—is more challenging. In this respect, the emerging remote sensing techniques discussed above provide a promising avenue forward.

8.3. What Are the Interactions Between Agricultural LULCC, Management, and Natural Vegetation and Ecosystems?

There has been much discussion surrounding the benefits and challenges of multifunctional, integrated agricultural/natural landscapes, and the efficacy of agricultural "land sharing" versus "land sparing" in providing a range of ecosystem services that also preserve biodiversity [*DeFries and Rosenzweig*, 2010; *Phalan et al*., 2011; *Tscharntke et al*., 2012]. While there are many elements of this debate that cannot yet be captured by ESMs, such as the explicit impacts to faunal biodiversity and human settlements, there is scope to explore a range of other interactions and make major contributions to this line of inquiry. These include, but are not limited to: the land surface-climate interactions resulting from different levels of "land sharing" versus "land sparing" and landscape multifunctionality; the impacts of landscape heterogeneity on biogeochemical cycling; resource (e.g., water) competition between managed crops and native species, particularly as it affects nutrient cycling in agricultural systems; and the potential of mixed natural-agricultural landscapes to exhibit more resilience to anthropogenic GHG-forced climate change. Currently, most coupled climate-crop ESMs separate the soil columns between natural and managed vegetation types, which minimize their interaction. However, near-future development efforts could experiment with allowing natural and managed vegetation types to exchange quantities, experience the effects of management processes, and utilize the same resource pools. In doing so, we can better explore and understand the complexity of coupled natural-managed landscapes, and assess their potential ecosystem services in the context of growing food demand and global environmental change.

8.4. How Might ESMs be Used to Evaluate Agricultural Strategies for Climate Change Mitigation?

To more fully explore this question, ESMs will need to develop in two ways: (1) improve and enhance model carbon and nitrogen cycling schemes, and (2) better incorporate global and regional agricultural management, particularly for large-scale agricultural systems. Furthermore, multimodel intercomparisons, such as LUMIP [*Lawrence et al*., 2016b], enable efficient and targeted development in these respects and the systematic identification of robust responses and outstanding uncertainties. This is critical to assessments of agricultural carbon sequestration, which will depend heavily on management techniques, LULCC, and climate interactions. Improved representations of agriculture-biogeochemical cycling will also require that models leverage improved spatial and temporal data sets of management practices. Doing so may also help to distinguish incentives and policy regimes conducive to carbon management.

To this end, ESMs should consider incorporating data sets and results associated with regional integrated assessments of food security and agricultural adaptation. This presents an opportunity to build linkages with on-going projects such as the Agricultural Model Intercomparison and Improvement Project (www.agmip.org) Regional Integrated Assessments [*Rosenzweig et al*., 2013], Coordinated Global and Regional Assessments (CGRA, [*Rosenzweig et al*., 2016]), and Global Gridded Crop Model Intercomparison [*Elliott et al*., 2015]. These efforts have collected much information on regional cropping systems and management, and are currently developing methodologies and best practices to scale their findings. Liaising with these initiatives could enable ESM groups to better incorporate heterogeneous, "real world" crop and management information into model frameworks. This is particularly needed in areas where management may have strong interactions with climate processes (e.g., irrigated areas in the semiarid tropics). These integrated assessments are also developing and evaluating potential adaptation strategies to climate change scenarios. Some strategies, such altered cropping systems or introduced irrigation, could eventually be incorporated into regional or high-resolution ESM simulations. In doing so, we may better assess their efficacy under climate change and their potential feedbacks on regional climate systems.

The Integrated Assessment Modeling (IAM) community tracks LULCC in response to particular scenarios of global development, and market and commodity demands. ESMs may then adapt these path-dependent LULCC for simulations with consistent pathways of anthropogenic emissions [*Moss et al*., 2010]. These land-use trajectories greatly influence regional market conditions, demand, and adaptation strategies, such as those being developed by the AgMIP RIAs. However, regional adaptations and incentives, such as buffering agricultural soil carbon, are also an important "feedback" to climate change and global development trends [*Hurtt et al*., 2011; *van Vuuren et al*., 2011b]. Therefore, ESMs could be further utilized in multimodel comparisons of alternative agroecosystem management options (e.g., "climate-smart" versus commodity-driven) under different development and emissions scenarios. However, current ESM-only comparisons would not offer the economic returns or trade-offs of alternative agroecosystem strategies. These trade-offs are a critical evaluation point when considering adaptation options and their adoption [e.g., *Grace et al*., 2012]. This limitation could be addressed by integrated modeling efforts, discussed below, which enable interactive simulation of both biophysical and socioeconomic feedbacks in response to various production systems [*Adam et al*., 2015; *Wang et al*., 2017]. In the meantime, ESMs can provide a generalized "environmental impacts assessment" for agricultural management options. Additionally, they could help identify the most (biophysically) effective management strategies to mitigate potential deleterious regional climate changes.

Finally, some agricultural LULCC are considered to be GHG "mitigating" in ways other than explicitly sequestering soil carbon. For example, RCP2.6—currently the most aggressive climate change mitigation scenario—requires increased land devoted to biofuel production [*van Vuuren et al*., 2011a]. Given current international agreements limiting warming to 2°C, the regional implications of increased biofuel production to meet this goal warrants further holistic study [*Georgescu et al*., 2011]. One avenue to do so with ESMs is to include and improve PFT parameterizations for biofuel crops. These include current biofuel sources (e.g., maize and sugarcane), or emerging alternatives, such as miscanthus, which has been recently developed for climate-crop modeling frameworks [e.g., *Robertson et al*., 2015]. However, such developments are largely constrained by data availability.

Where data are increasingly available, ESMs may be leveraged for more targeted assessments of commercial crops planted over large areas. For example, the rapid Indonesian oil palm expansion rate, nearly 10%/year, has exacerbated regional deforestation and incurred significant carbon losses. To better understand the biophysical impacts, *Fan et al*. [2015] developed specific growth and nutrient cycling parameterizations for the CLM4.5. Such developments enable a range of regional and global climate assessments pertinent to evaluating oil palm sustainability. These include the GHG impacts of land appropriation for oil palm, the impact of its management on nutrient and water cycling, and interactions with the regional climate system and processes [*Fan et al*., 2015].

8.5. What Is the Role of Human Decision-Making in ESM Representation of Agriculture?

Ultimately, human decision-making is the prime driver of agriculture's extent, intensity, and variability. Agricultural decision-making is governed by a range of pressures: climatic and meteorological, socioeconomic, political, and even cultural [*Porter et al*., 2014]. As such, capturing the full range of possible agricultural decision-making in an ESM presents a challenging task. Uncertainties exist in both the climate and agricultural responses (e.g., the decision to switch crops), and the driving assumptions (e.g., economics dominate farmer decision-making). Nevertheless, as ESMs incorporate agriculture in increasing detail, more discussion is warranted on what constitutes an “adequate representation” for climate simulation. Additionally, the ESM community should define the intended utility of fully coupled climate-agricultural models for particular user communities (e.g., scientific versus stakeholder).

The ESM studies summarized herein represent agricultural decision-making as implicit and/or prescribed. This is largely based on available agricultural data, which often excludes the full range of observed variation. As an alternative, coordinated sensitivity tests with these model capacities would help bracket climate responses to temporal and spatial variations in agricultural management. Such testing will help identify management components that are most impactful to regional climate systems. ESMs might then focus development on those specific management options to reflect real-time decision-making in response to climate-agriculture feedbacks.

However, some important agricultural decision-making components are externally driven. For example, the choice of crop and cropping system is sensitive to regional and global agricultural markets, pricing, institutional structures (e.g., crop insurance), incentives (e.g., payments for ecosystem services), as well as climate. Thus, the full integration of ESMs with sectoral impact models, economic models, and/or IAMs, is another potential development trajectory to resolve climate-agriculture-development interactions in real-time [*Adam et al*., 2015; *Collins et al*., 2015b; *Wang et al*., 2017]. Interactive simulations of biophysical agricultural impacts, natural resources, and economic development are increasingly emphasized in emerging “food-energy-water nexus” research efforts [*Bazilian et al*., 2011]. Integrated modeling could produce more comprehensive scenarios of anthropogenic emissions and global environmental change that include intersectoral feedbacks [*Di Vittorio et al*., 2014; *Collins et al*., 2015b]. These frameworks can also help quantify the relative roles of socioeconomic development and climate change in driving regional agricultural LULCC [*Wang et al*., 2017]. Where driving data are readily available, integrated models could also serve stakeholders as a decision-support tool to evaluate intersectoral trade-offs between food, energy, and water [*Adam et al*., 2015]. However, many uncertainties remain among these disparate models, their assumptions, and driving data sets, which make their impact on climate systems difficult to discern [*Rötter et al*., 2011; *van Vuuren et al*., 2012; *Nelson et al*., 2014]. Thus, a critical view must be taken when evaluating and deriving meaning from the simulated results, especially if applied to stakeholder contexts.

Finally, further discussion is warranted on how, and whether, ESMs should be used to predict crop yields as a source of decision support. The constraints on important crop-growth parameterizations discussed in section 5.1 are an outstanding challenge for ESM yield-based assessments. There is also a need to carefully consider any diminishing returns that accompany increasingly complex agricultural representations. This is particularly important given that other highly uncertain, but significantly impactful, climate system components demand further ESM development resources (e.g., land ice sheets).

9. Concluding Remarks

We herein reviewed the current approaches for incorporating agricultural management and land-use in advanced ESMs in order to capture climate-relevant interactions with water resources, energy balance, and biogeochemical cycling. These methods range from prescribed, idealized approaches that include land surface conversions, transitions, and management components such as irrigation, to dynamic climate-crop models that evaluate the “real-time” crop response to changing climate conditions.

The proposed next steps in incorporating agriculture into ESMs should be to better integrate regionally representative management practices, with an emphasis on water resources used for irrigation and agroecosystem carbon cycling and nutrient management. Current coordinated model intercomparison and benchmarking initiatives, along with ongoing data collection efforts, may be leveraged to help facilitate development of these capacities. While detailed regional data on time-varying management has been sparse, more recent data collection and remote sensing efforts will prove essential to ESM agricultural representations and model validation. Finally, improving and coordinating agricultural representation in ESMs will enable sensitivity testing for a range of management conditions and adaptation options. These new ESM capacities will advance our understanding on how various agricultural management and landuse practices affect critical ecosystem services, climate feedbacks, and can potentially contribute to climate change mitigation efforts.

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