Evaluating the Crop Productivity under Variable and Changing Climate: An Integrated Data-Modeling Approach

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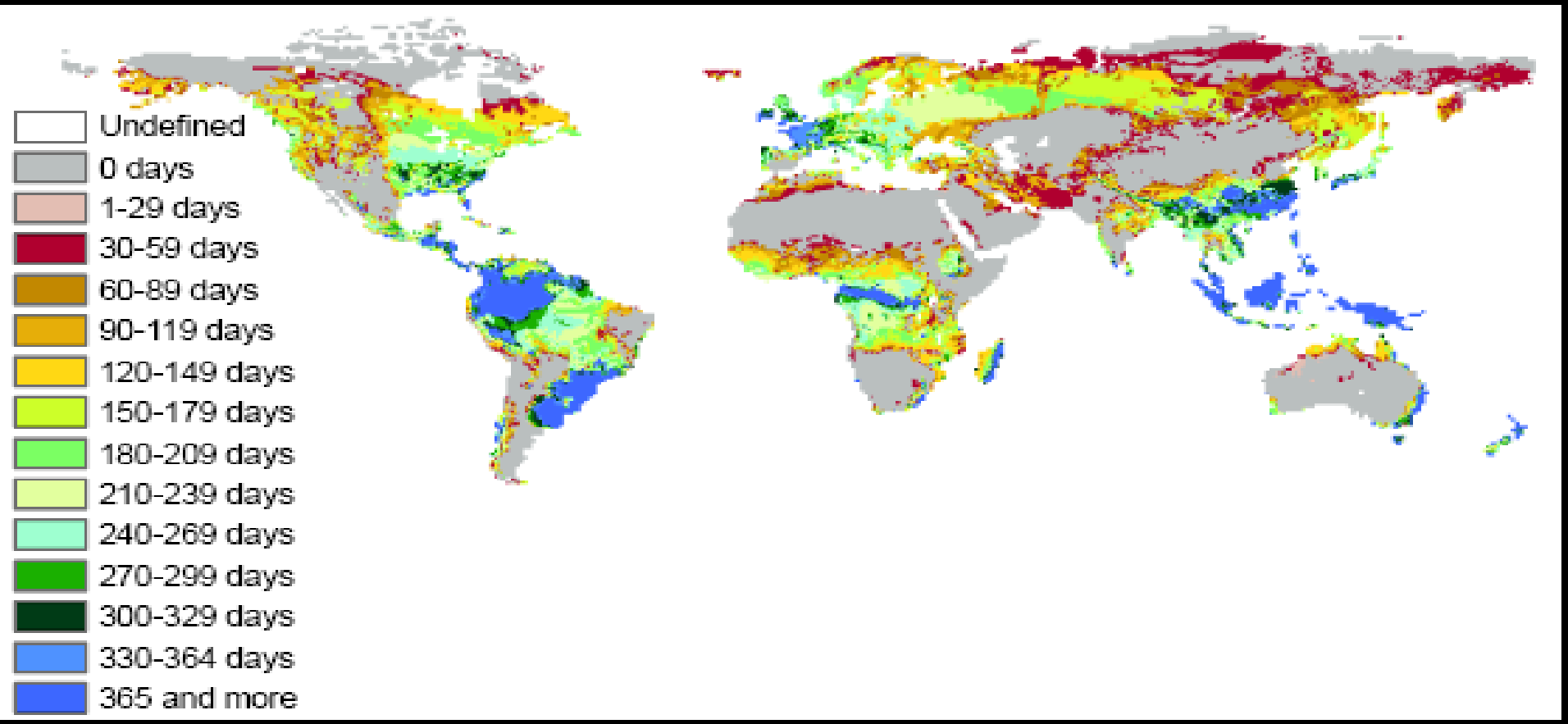
Acknowledgements

Yang Song (ORNL) & Prasanth Meiyappan (Amazon.com)
NASA & NSF

Length of Growing Period - Year 2000



Background

Four principal objectives

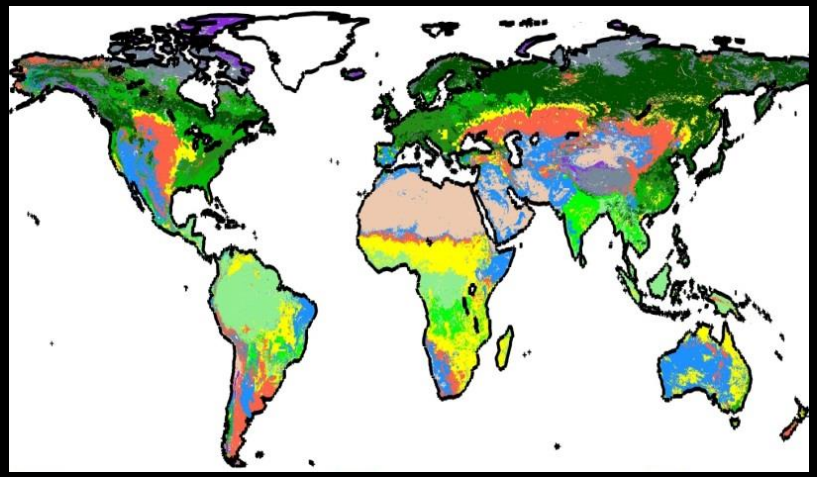
To understand the major LCLUC transition activities in the study region.

To advance our understanding of the causes of LCLUC.

To improve our understanding of the historical effects of LCLUC dynamics on the quantities and pathways of terrestrial carbon and nitrogen fluxes.

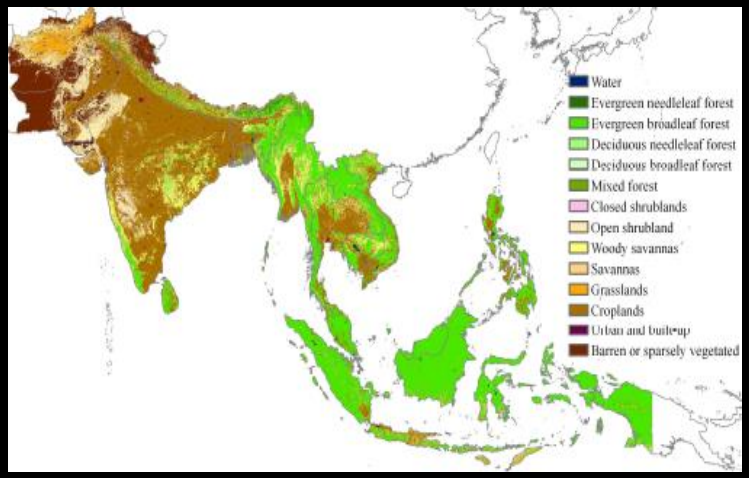
To understand the impact of climate change and variability on terrestrial ecosystem productivity

Impact of Land Cover and land Use Change on Biogeophysics and Biogeochemistry : ISAM Approach

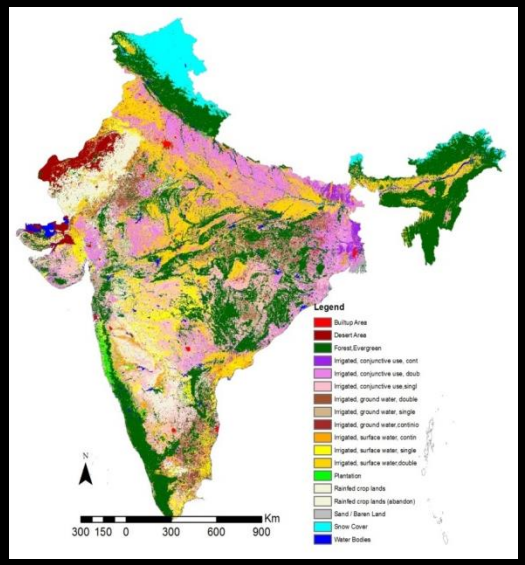


Global Scale

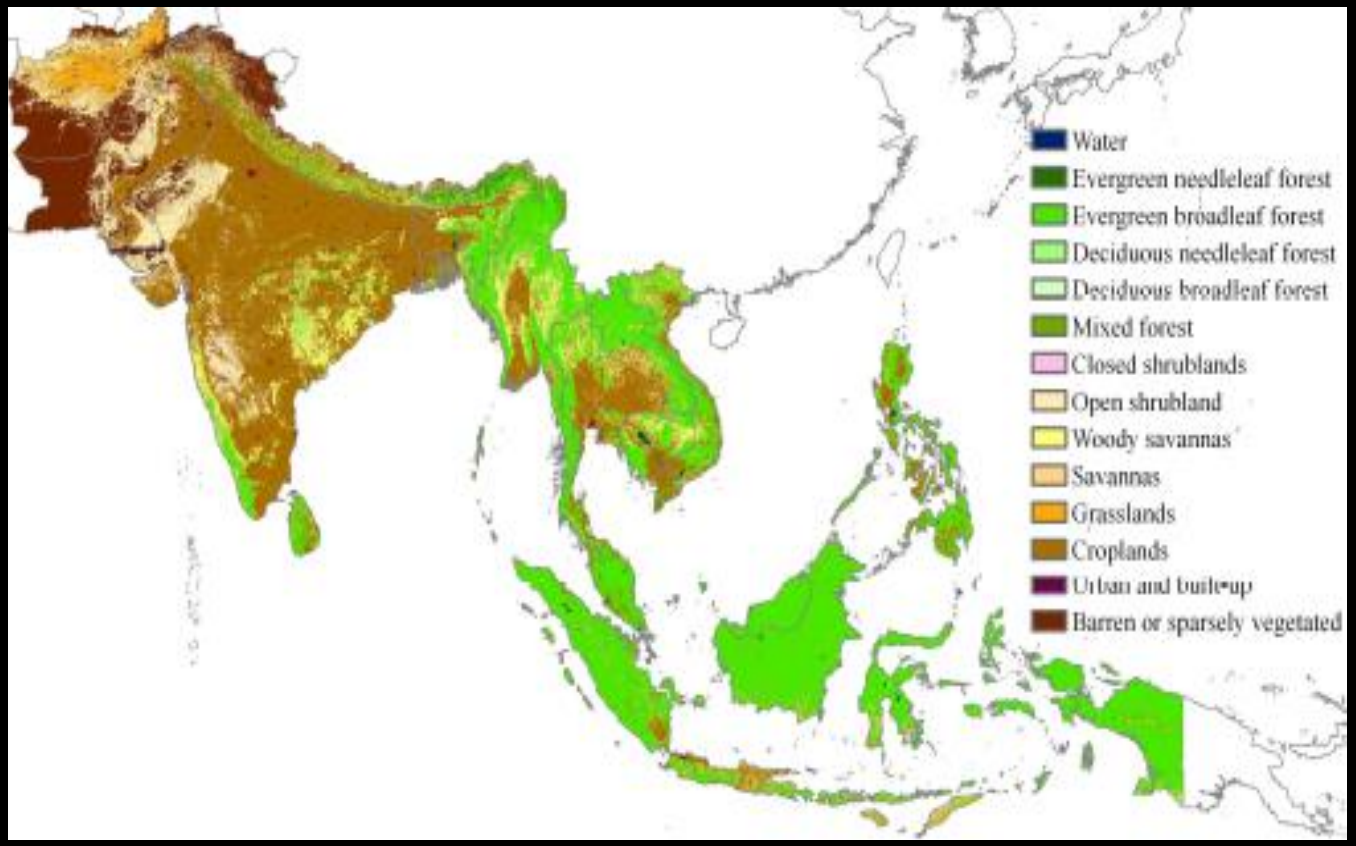
Regional Scale



National Scale



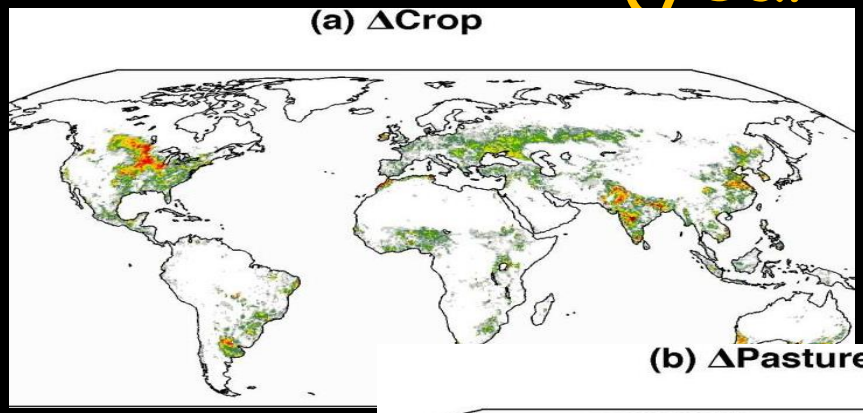
SSEA Region

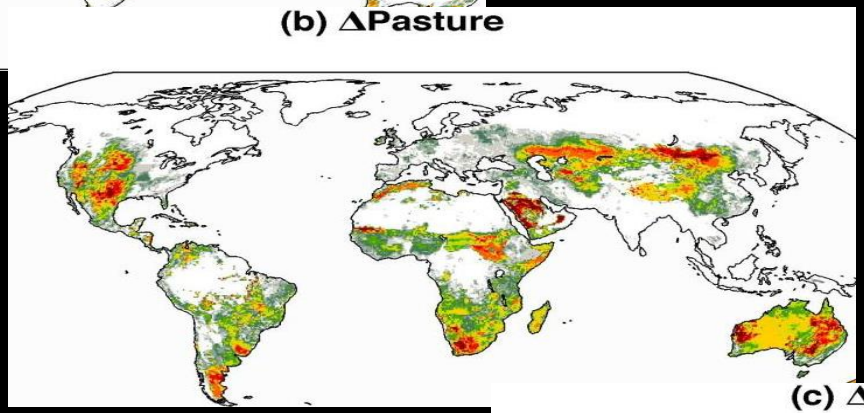


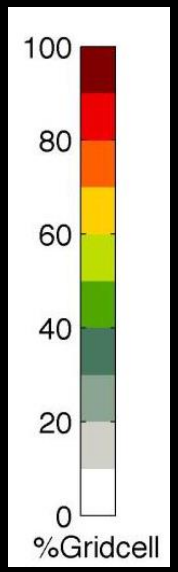
LCLUC distribution in the study region

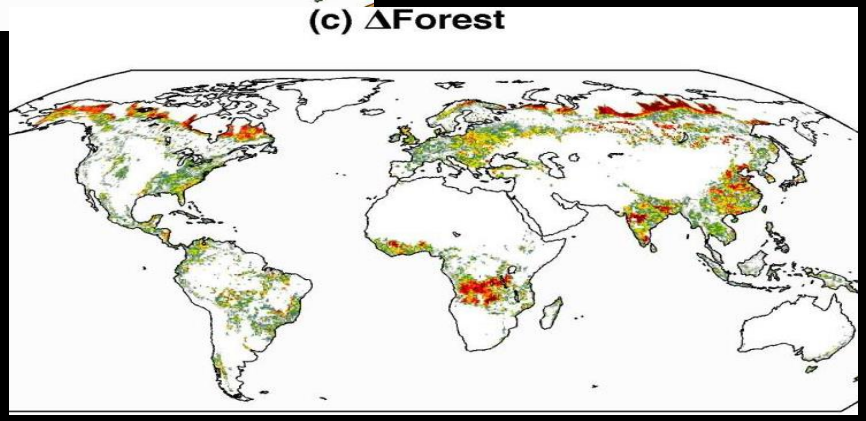
- Covers about 16% of earth's land surface
- Characterized by a long history of LCLUC activities
- the home for over 50% of the world's population
- ***Study LCLUC dynamics country-by-country basis***

Maximum grid-level differences using Various Realizations of LCLUC (year 2005)









Various Realizations:

- HYDE
- SAGE (RF)
- Houghton (HH)
- Satellite data sets

Remote Sens. **2015**, *7*, 2401-2430; doi:10.3390/rs70302401

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remote sensing

ISSN 2072-4292

www.mdpi.com/journal/remotesensing

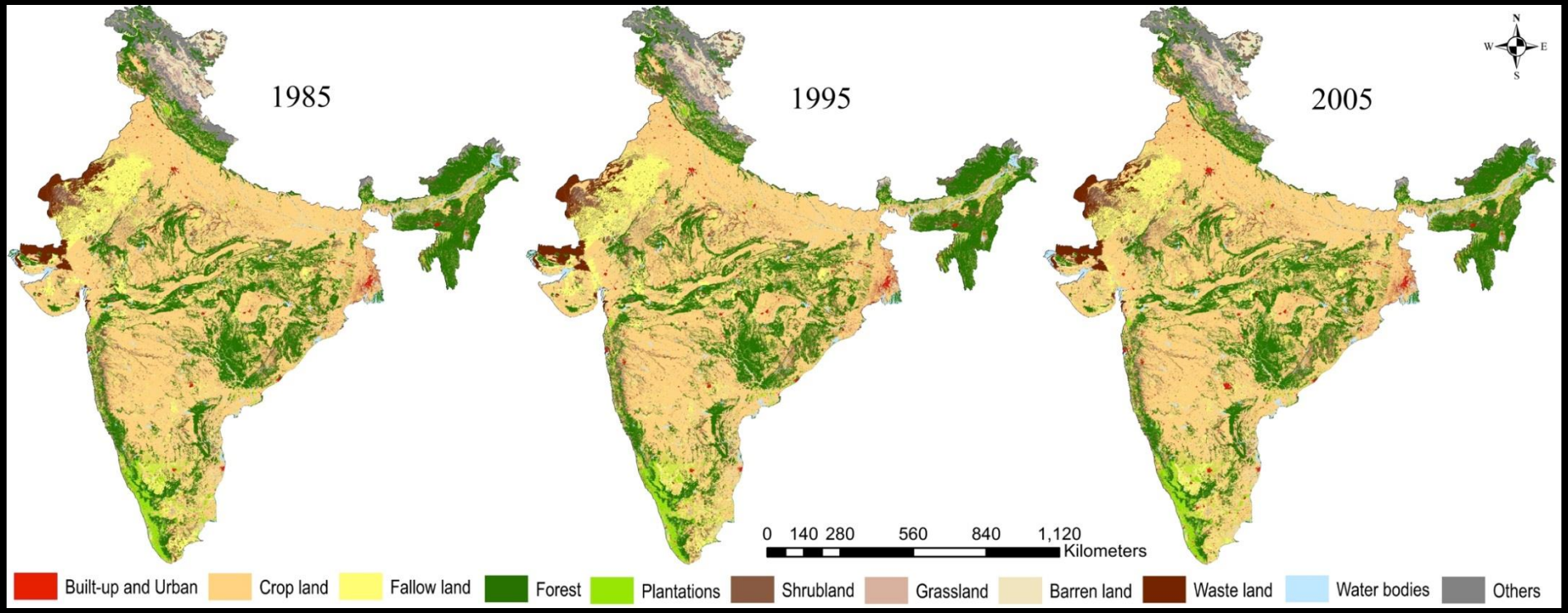
Article

Development of Decadal (1985–1995–2005) Land Use and Land Cover Database for India

Parth S. Roy [1,*,†], Arijit Roy [2,†], Pawan K. Joshi [3,†], Manish P. Kale [4,†], Vijay K. Srivastava [5,†], Sushil K. Srivastava [2,†], Ravi S. Dwevidi [5,†], Chitiz Joshi [2,†], Mukunda D. Behera [6,†], Prasanth Meiyappan [7], Yeshu Sharma [1], Atul K. Jain [7,*], Jamuna S. Singh [8], Yajnaseni Palchowdhuri [9], Reshma. M. Ramachandran [1], Bhavani Pinjarla [1], V. Chakravarthi [1], Nani Babu [10], Mahalakshmi S. Gowsalya [11], Praveen Thiruvengadam [11], Mrinalni Kotteeswaran [11], Vishnu Priya [12], Krishna Murthy V. N. Yelishetty [2], Sandeep Maithani [2], Gautam Talukdar [13], Indranil Mondal [13], Krishnan S. Rajan [14], Prasad S. Narendra [15], Sushmita Biswal [3], Anusheema Chakraborty [3], Hitendra Padalia [2], Manoj Chavan [4], Satish N. Pardeshi [4], Swapnil A. Chaudhari [4], Arur Anand [16], Anjana Vyas [9], Mruthyunjaya K. Reddy [17], M. Ramalingam [18], R. Manonmani [18], Pritiranjan Behera [6], Pulakesh Das [6], Poonam Tripathi [6], Shafique Matin [6], Mohammed L. Khan [19], Om P. Tripathi [20], Jyotihman Deka [20], Prasanna Kumar [21] and Deepak Kushwaha [1]

Wall-to-wall Landsat Analysis (30m)

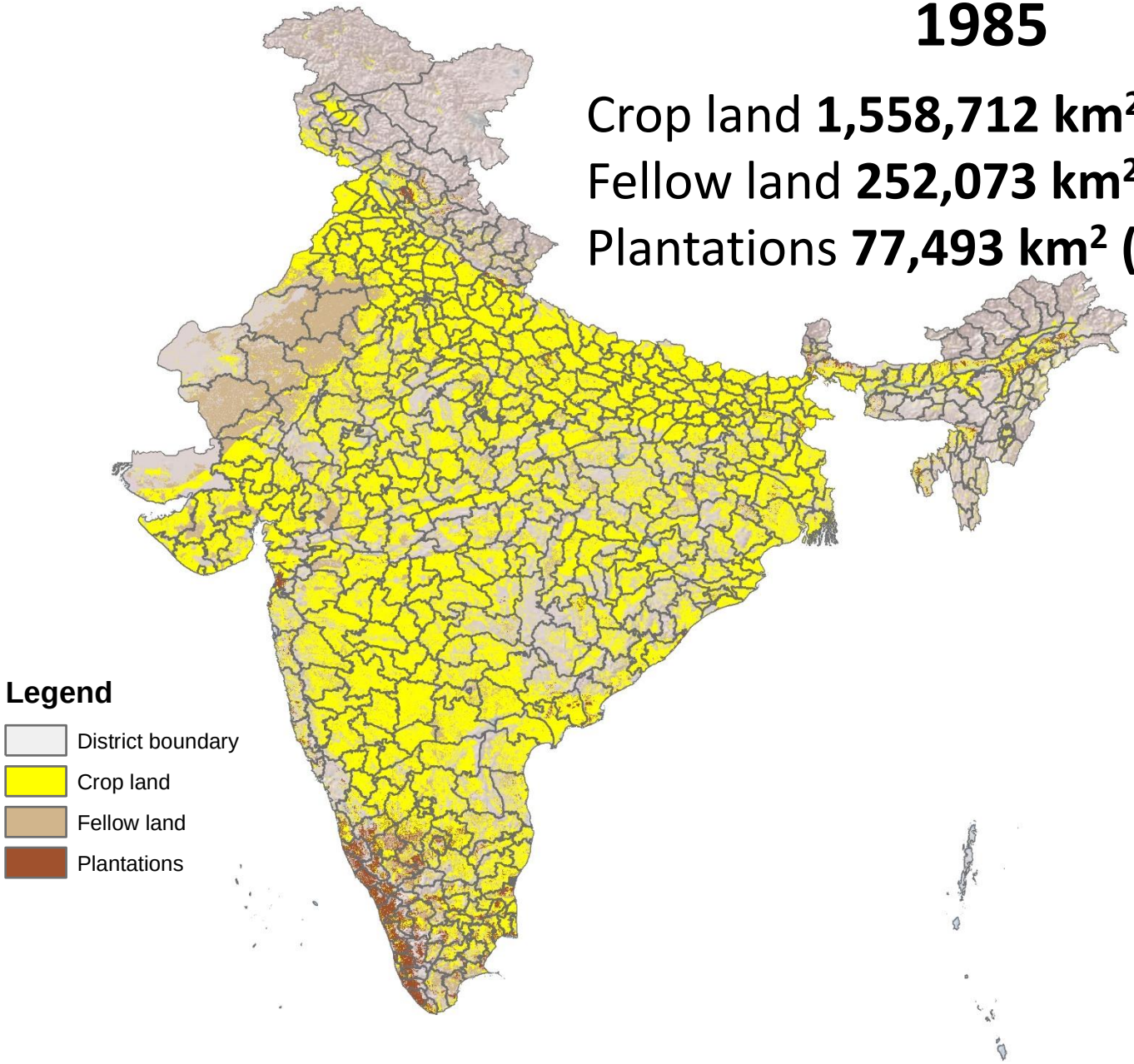
- Covers Longer Time Period: Decadal (1985-1995-2005)
- Uniform Classification Scheme: IGBP
- Patch to Patch Land Dynamics
- Ground Validation (>12000 points)



Roy et al. (*Remote Sensing*, 2015)

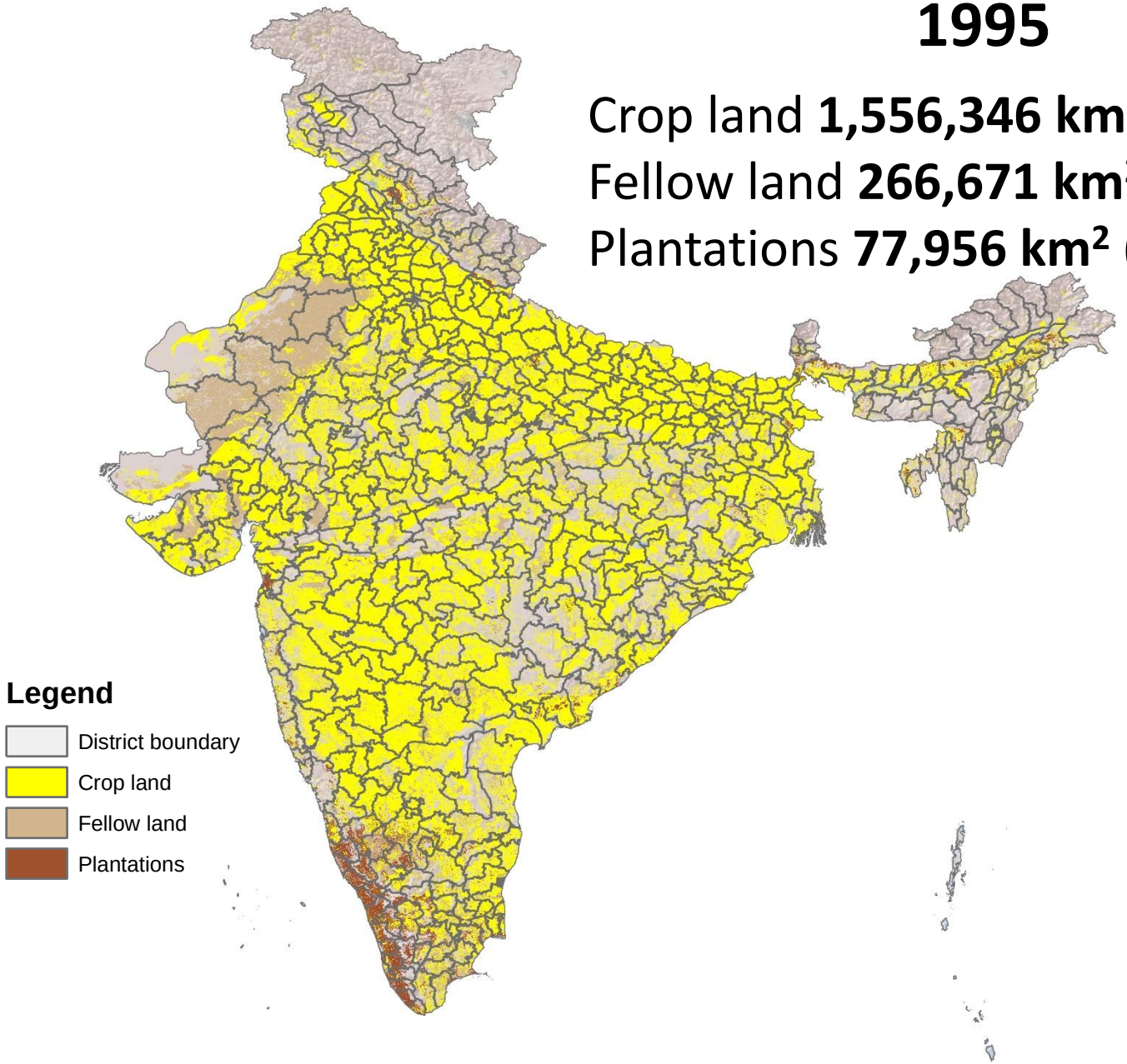
1985

Crop land **1,558,712 km^2 (47.55%)**
Fellow land **252,073 km^2 (7.86%)**
Plantations **77,493 km^2 (2.36%)**



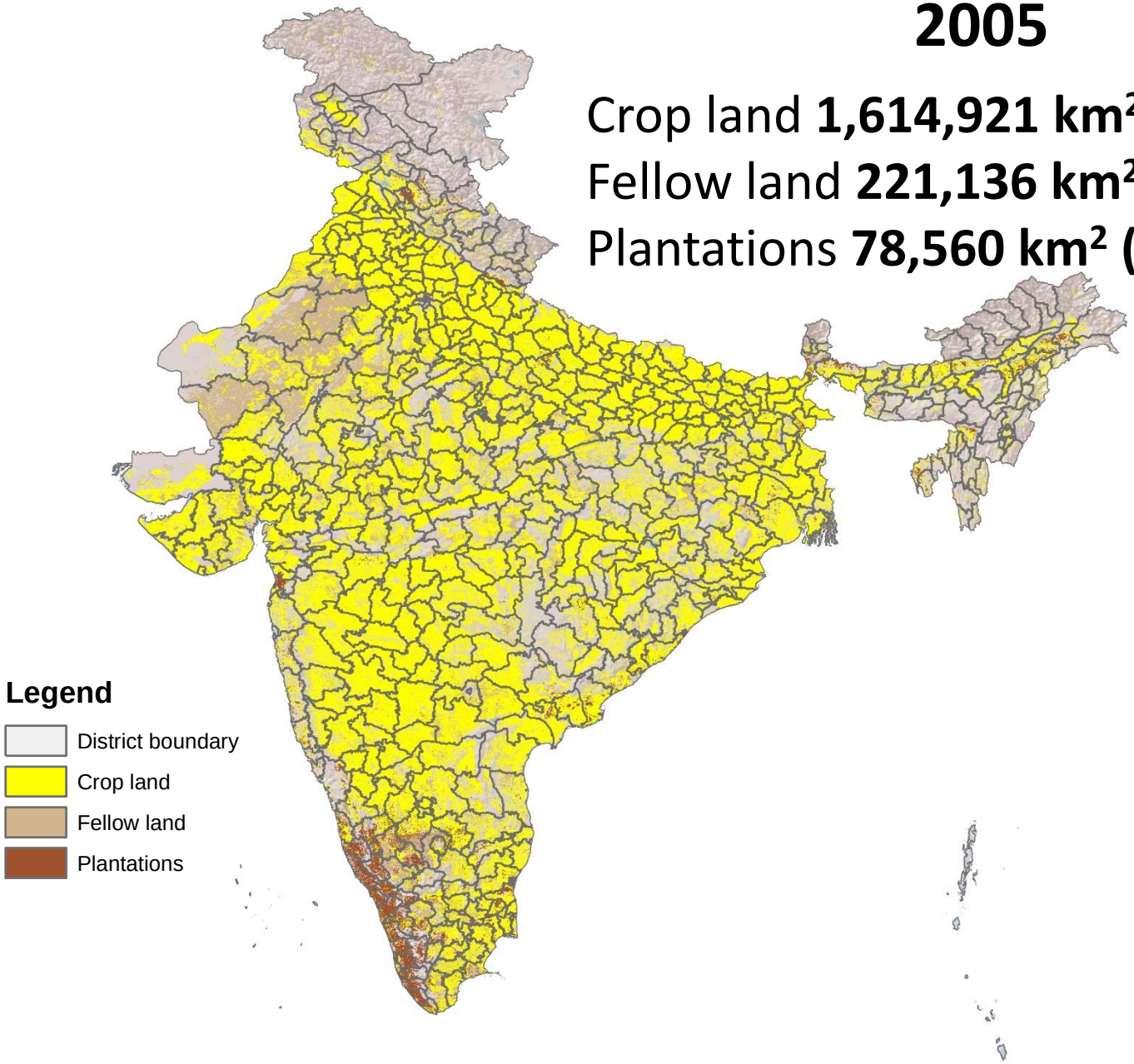
1995

Crop land **1,556,346 km^2 (47.45%**
Fellow land **266,671 km^2 (8.13%)**
Plantations **77,956 km^2 (2.37%)**

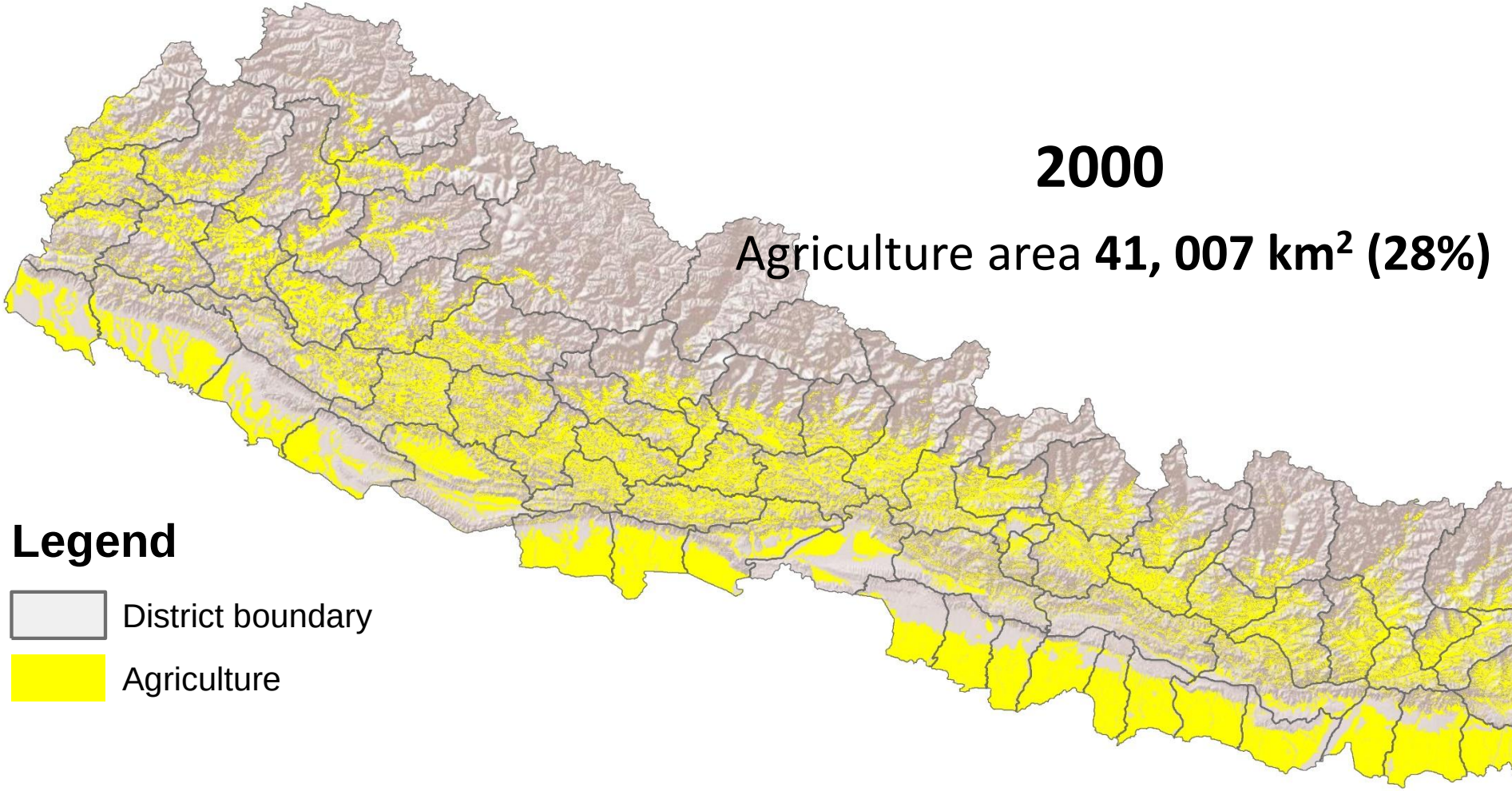


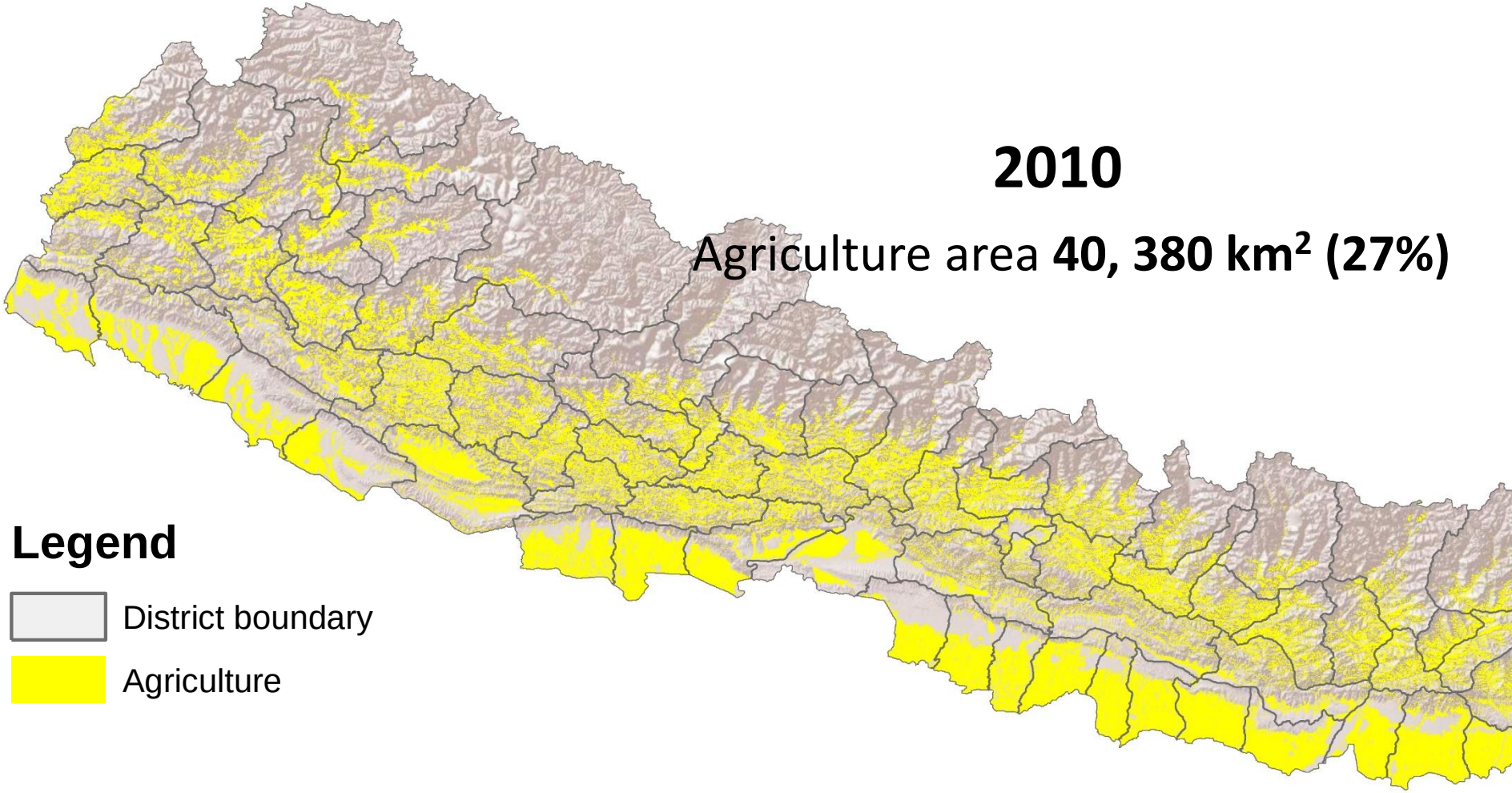
2005

Crop land **1,614,921 km² (49.34%)**
Fellow land **221,136 km² (6.77%)**
Plantations **78,560 km² (2.38%)**



NEPAL

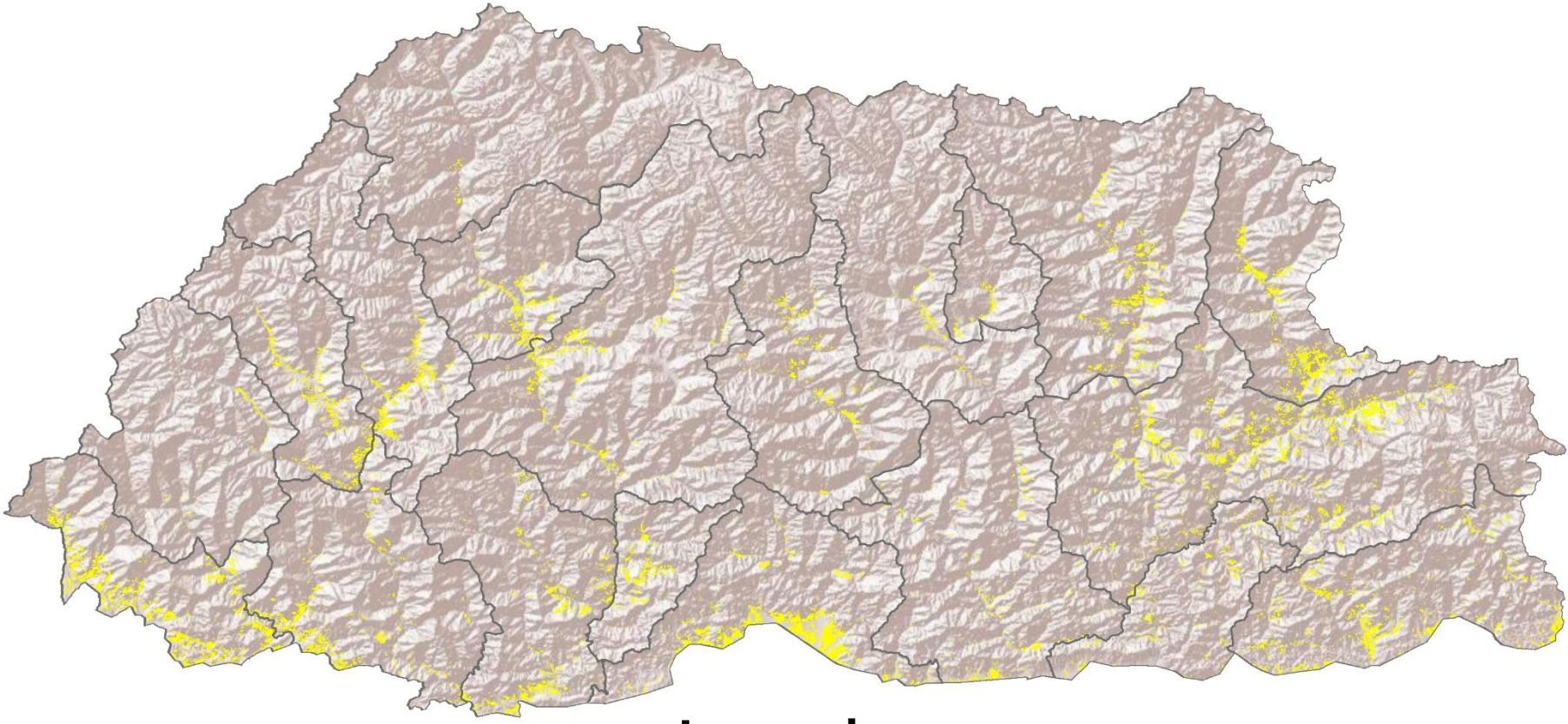

2000
Agriculture area **41, 007 km² (28%)**
Legend
District boundary
Agriculture


2010
Agriculture area 40, 380 km² (27%)
Legend
District boundary
Agriculture

Bhutan

1990

Agriculture area **1,144 km^2 (2.98%)**



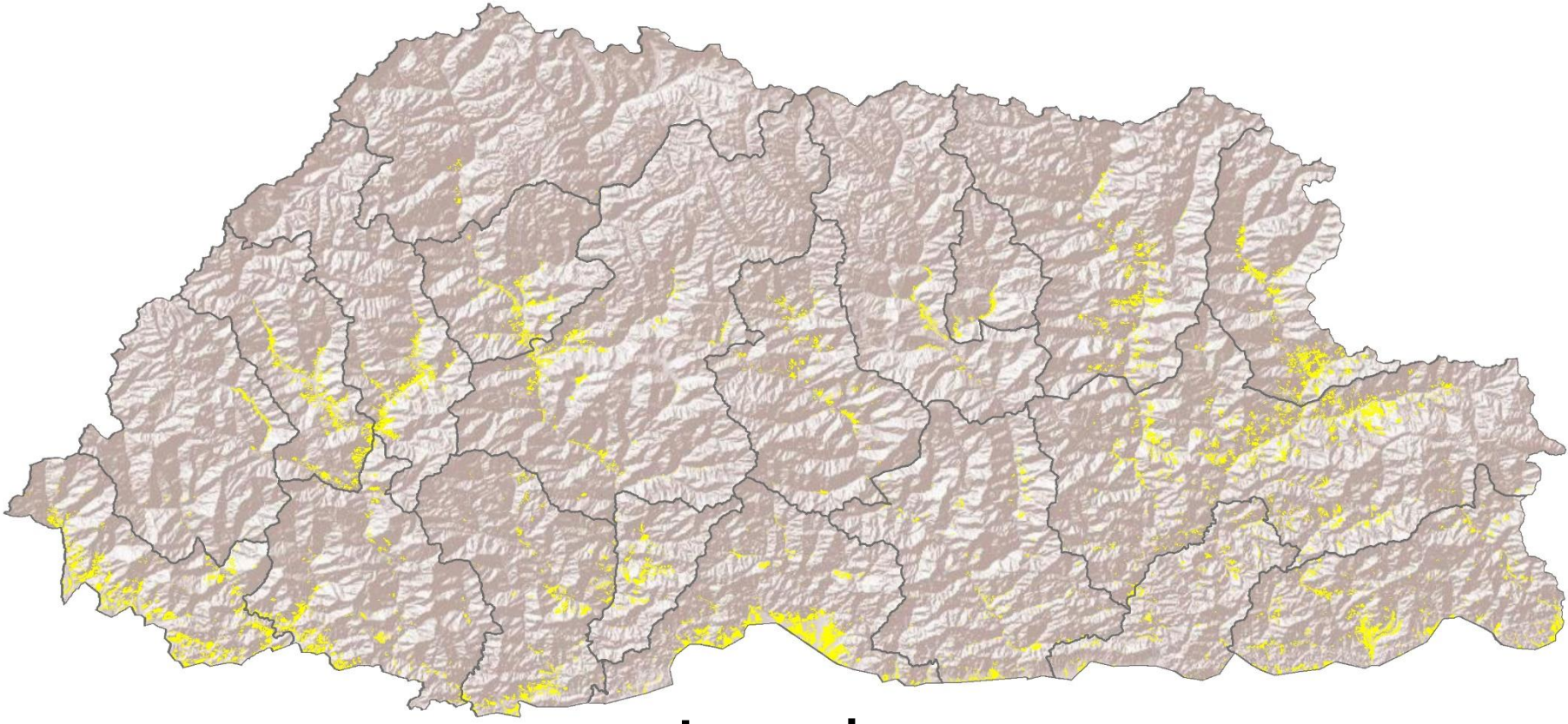
Legend

District boundary

Agriculture

2010

Agriculture area **1,200 km^2 (3.13%)**



Legend

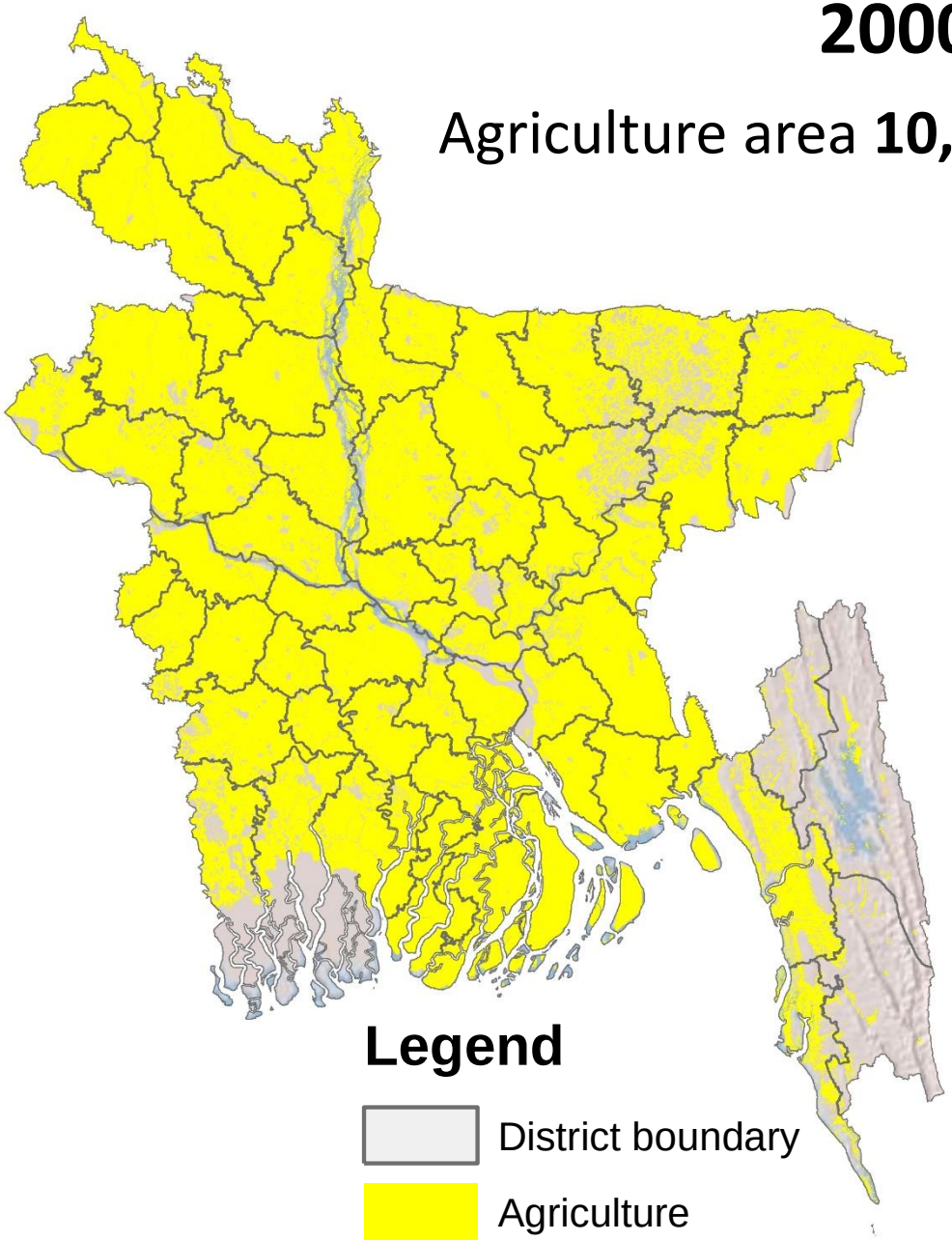
District boundary

Agriculture

Bangladesh

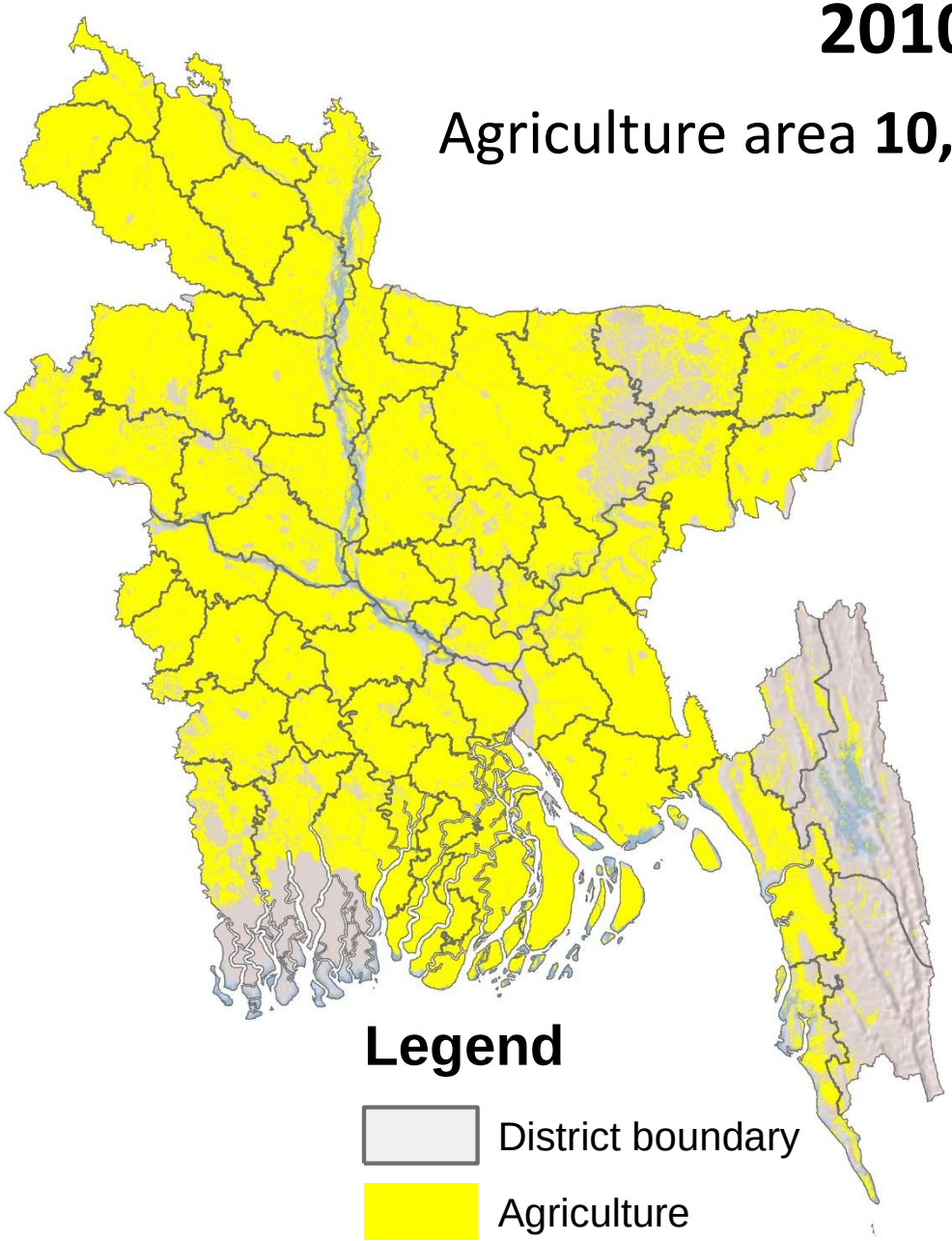
2000

Agriculture area **10,6610 km^2 (72%**

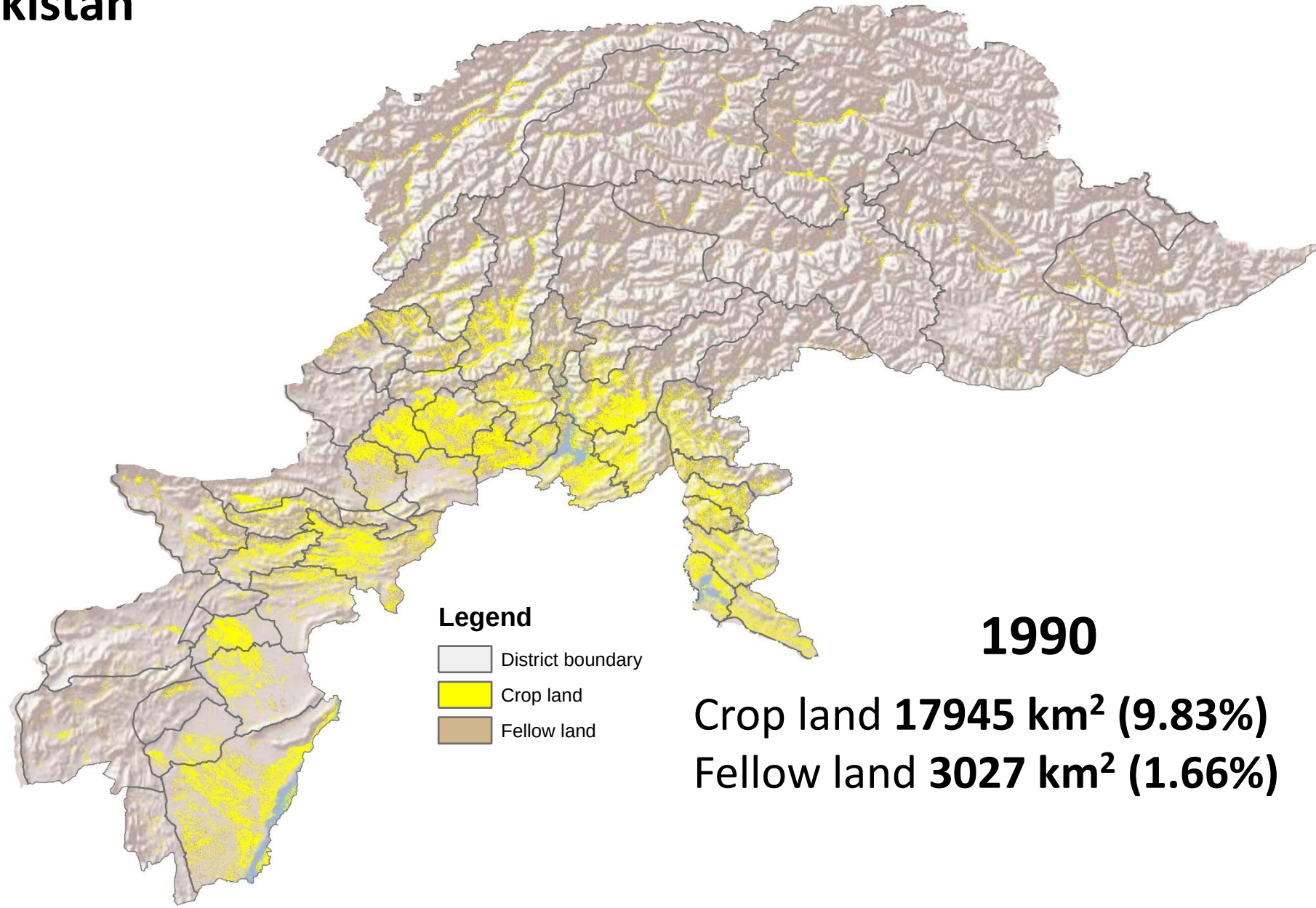


2010

Agriculture area **10,3520 km^2 (70%**



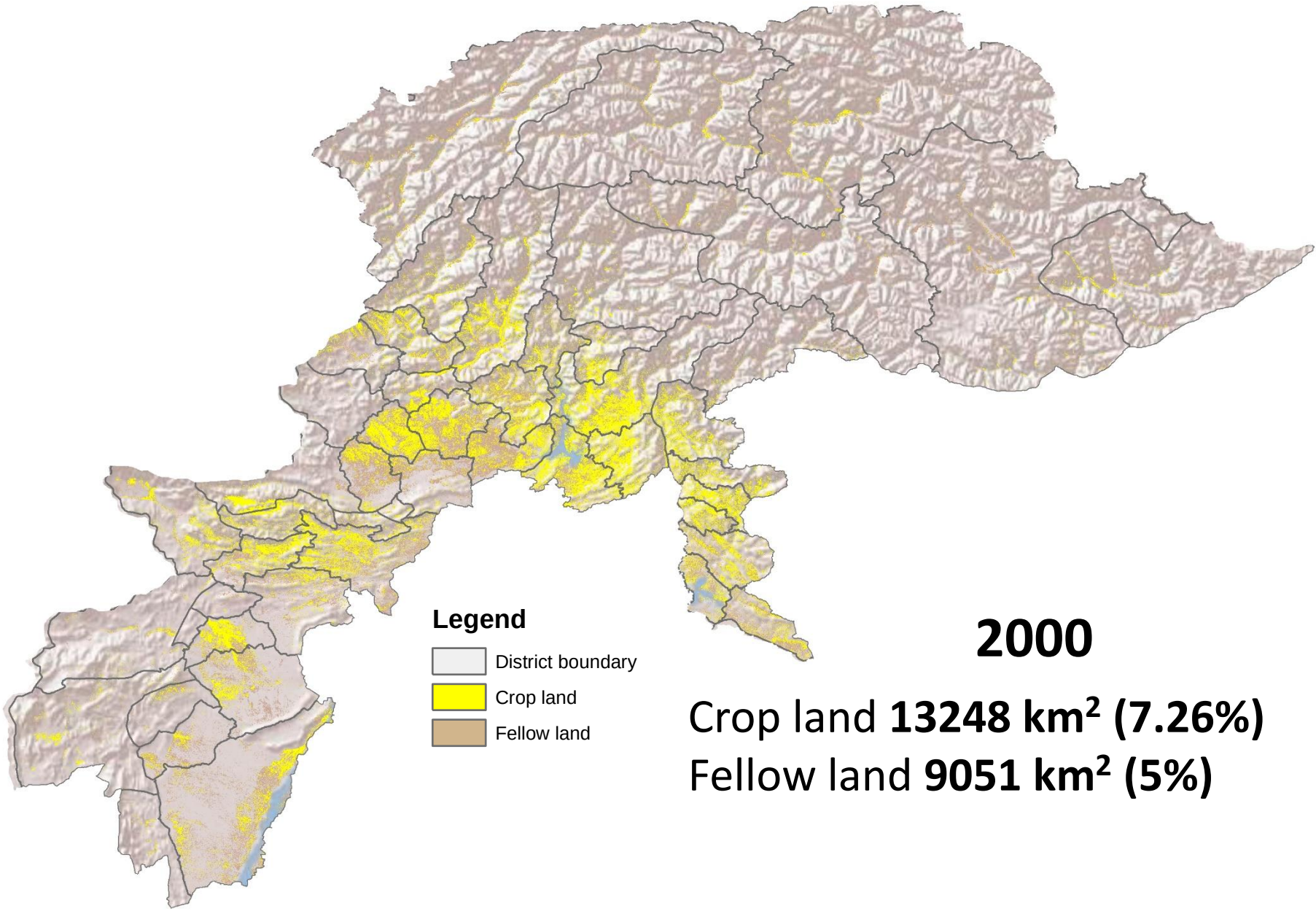
Pakistan



1990

Crop land **17945 km^2 (9.83%)**

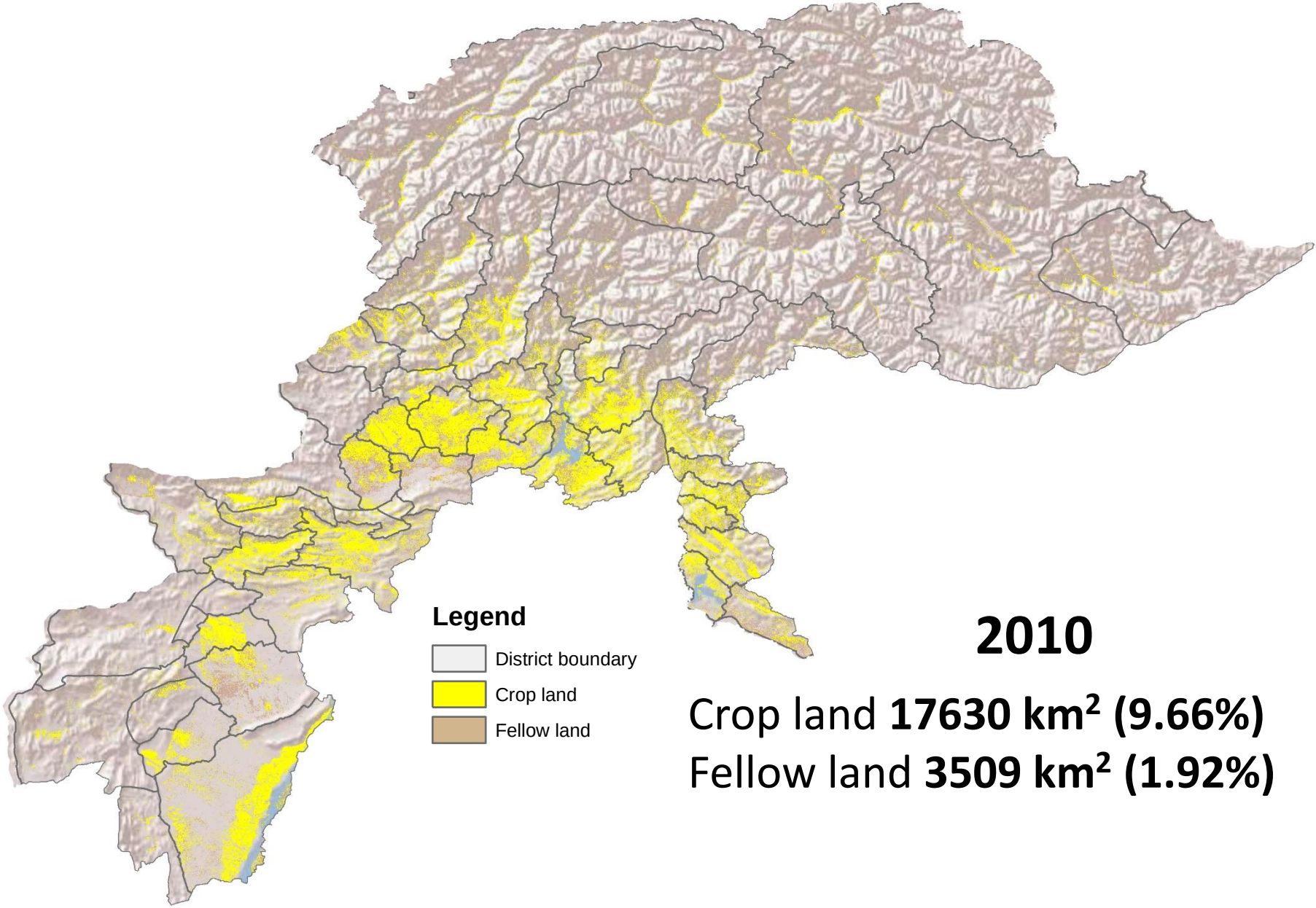
Fellow land **3027 km^2 (1.66%)**



2000

Crop land **13248 km^2 (7.26%)**

Fellow land **9051 km^2 (5%)**



2010

Crop land **17630 km^2 (9.66%)**

Fellow land **3509 km^2 (1.92%)**

Front. Earth Sci. , 6(2): 122–139
DOI 10.1007/s11707-012-0314-2

RESEARCH ARTICLE

Three distinct global estimates of historical land-cover change and land-use conversions for over 200 years

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Department of Atmospheric Sciences, University of Illinois, Urbana, IL 61801, USA

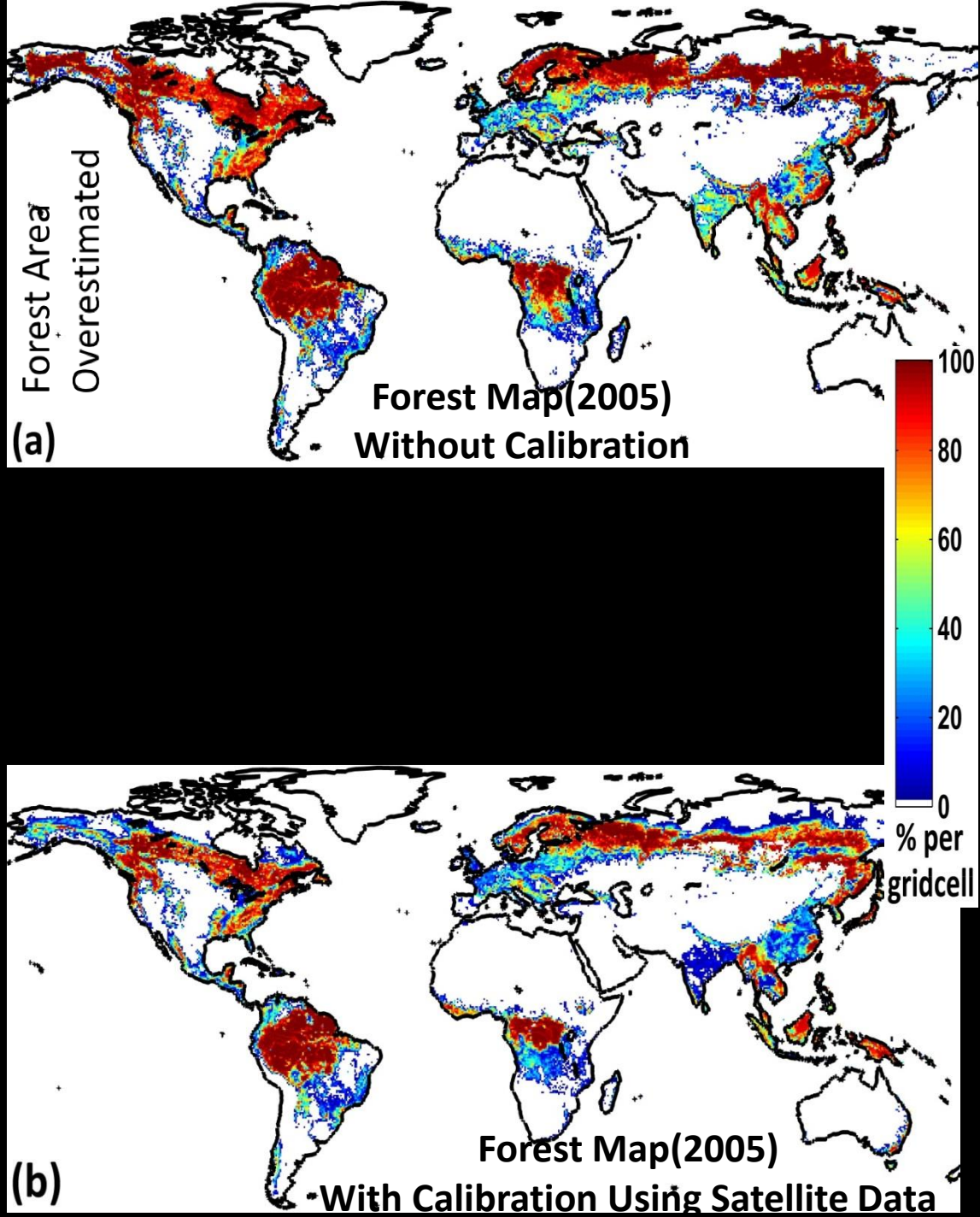
National Oceanic and Atmospheric Administration, Department of Commerce

Dataset

Historical Land-Cover Change and Land-Use Conversions Global Dataset

Updated: Feb 02, 2015

A set of three estimates of land-cover types and annual transformations of land use are provided on a global 0.5 x0.5 degree lat/lon grid at annual time steps. The longest of the three estimates spans 1770-2010. The dataset presented here takes into account land-cover change due to four major land-use/management activities: (1) cropland expansion and abandonment, (2) pastureland expansion and abandonment, (3) urbanization, and (4) secondary forest regrowth due to wood harvest. Due to uncertainties associated with estimating historical agricultural (crops and pastures) land use, the study uses three widely accepted global reconstruction of cropland and pastureland in combination with common wood harvest and urban land data set to provide three distinct estimates of historical land-cover change and underlying land-use


Forest Area
Overestimated
(a)
Forest Map(2005)
Without Calibration
100
80
60
40
20
0
% per
gridcell
(b)
Forest Map(2005)
With Calibration Using Satellite Data

Ecological Modelling 291 (2014) 152–174

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

Spatial modeling of agricultural land use change at global scale

Prasanth Meiyappan[a,*], Michael Dalton[b], Brian C. O'Neill[c], Atul K. Jain[a,**]

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[b] Alaska Fisheries Science Center, National Ocean and Atmospheric Administration, National Marine Fisheries Service, Seattle, WA 98115, USA
[c] Climate and Global Dynamics Division, National Center for Atmospheric Research, Boulder, CO 80307, USA

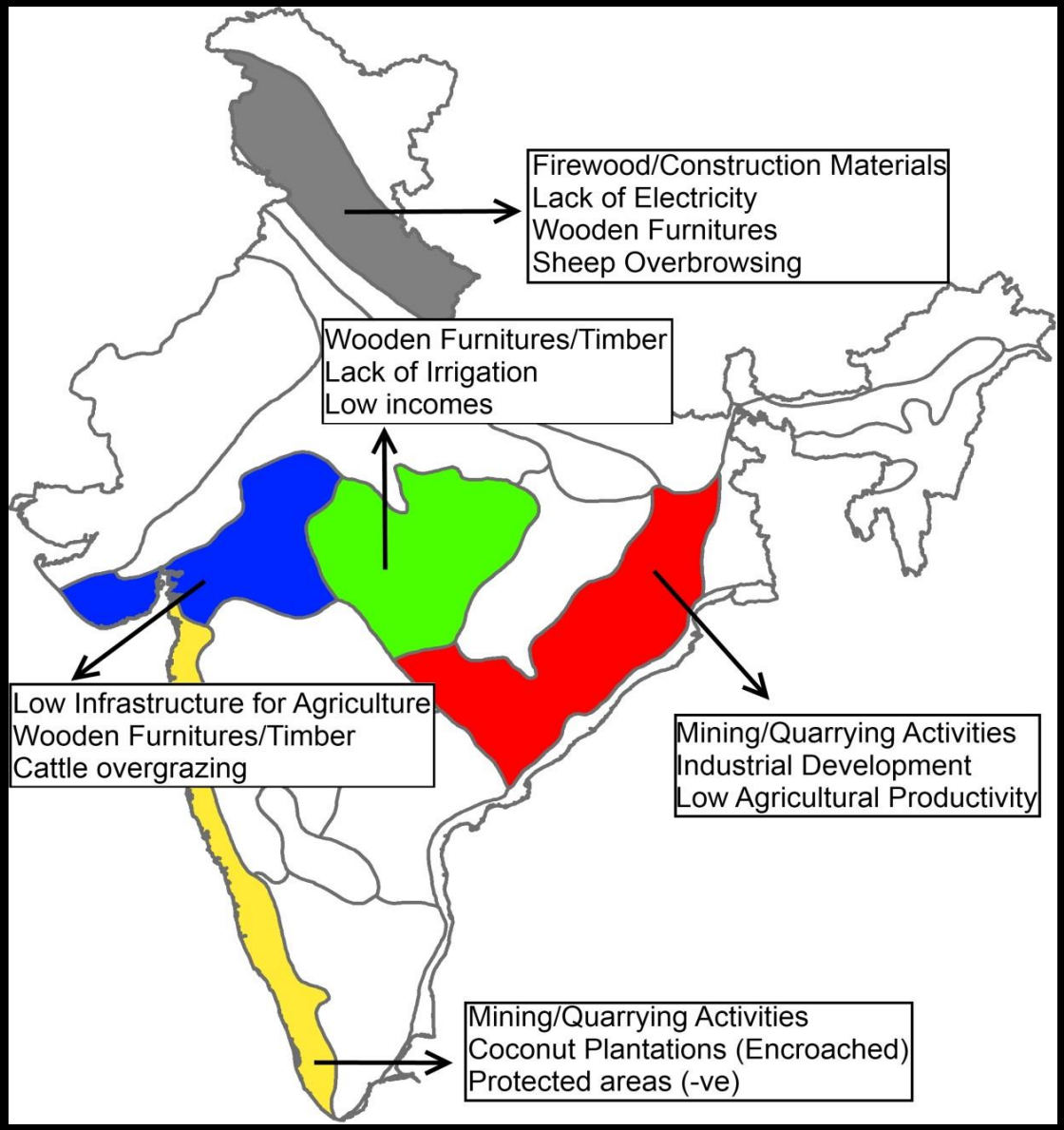
Reg Environ Change
DOI 10.1007/s10113-016-1068-2

ORIGINAL ARTICLE

Dynamics and determinants of land change in India: integrating satellite data with village socioeconomics

Prasanth Meiyappan[1] · Parth S. Roy[2] · Yeshu Sharma[3] · Reshma M. Ramachandran[2] · Pawan K. Joshi[4] · Ruth S. DeFries[5] · Atul K. Jain[1]

Summary of model findings (regional hotspots)



Meiyappan et al. (2015)

IOP Publishing Environ. Res. Lett. 11 (2016) 105006 doi:10.1088/1748-9326/11/10/105006

Environmental Research Letters

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7 April 2016

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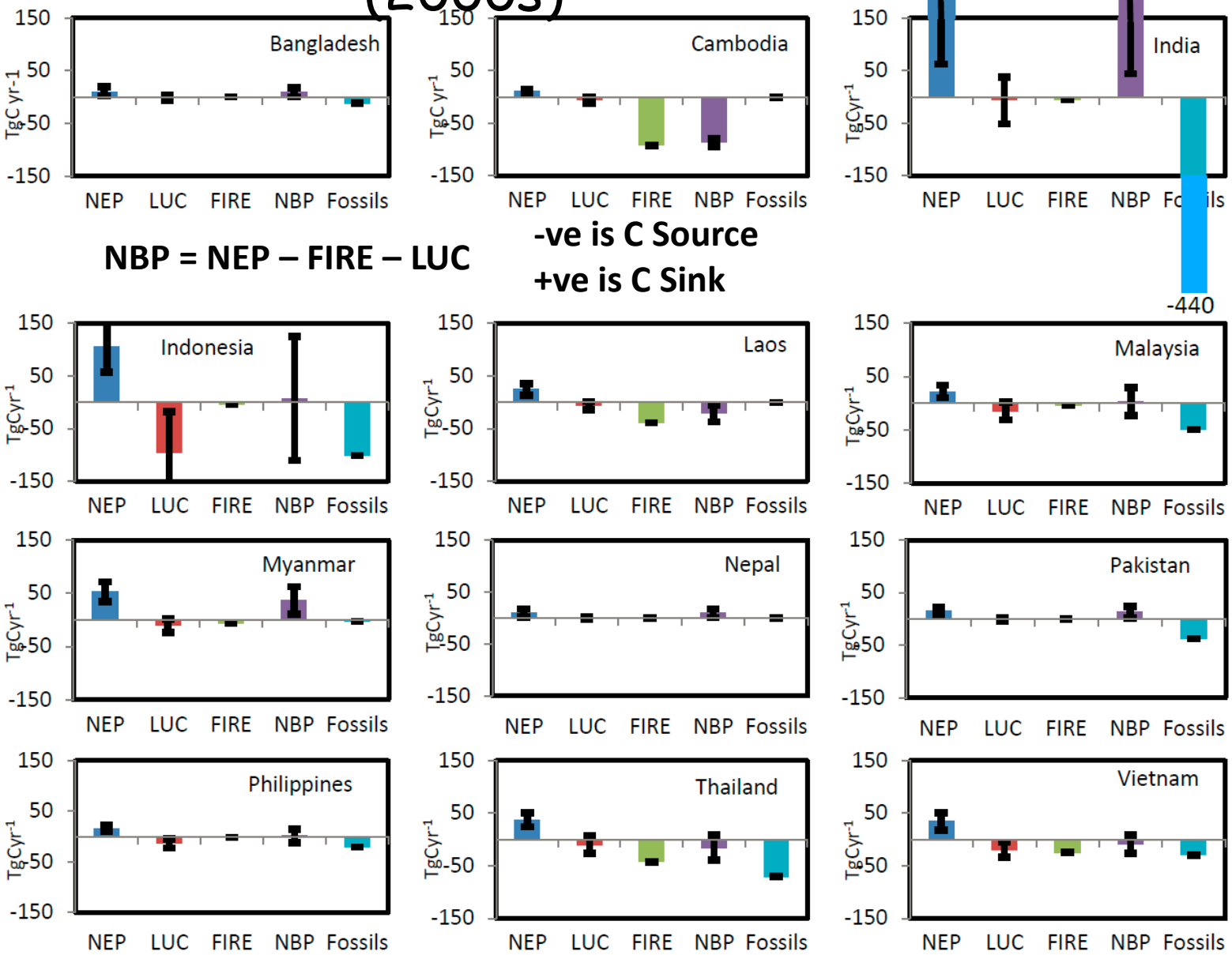
LETTER

The terrestrial carbon budget of South and Southeast Asia

Matthew Cervarich[1], Shijie Shu[1], Atul K Jain[1,15], Almut Arneth[2], Josep Canadell[3], Pierre Friedlingstein[4], Richard A Houghton[5], Etsushi Kato[6], Charles Koven[7], Prabir Patra[8], Ben Poulter[9], Stephen Sitch[10], Beni Stocker[11], Nicolas Viovy[12], Andy Wiltshire[13] and Ning Zeng[14]

Carbon Budget for SSEA countries (2000s)



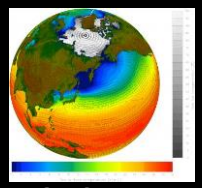
NBP = NEP – FIRE – LUC

-ve is C Source

+ve is C Sink

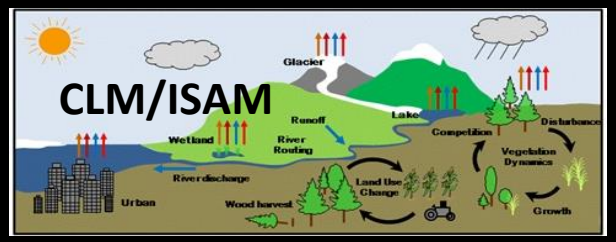
Cervarich et al. 2016

iPETS Baseline Scenario
SSP5, No climate change

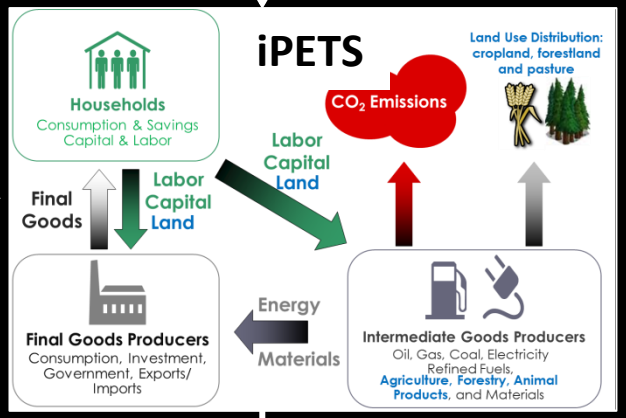


Climate change scenario

CESM

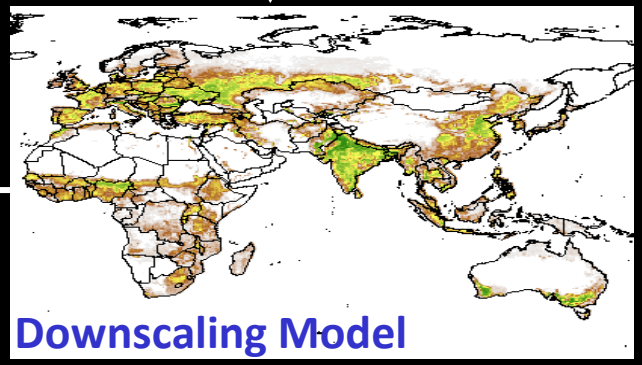


Aggregated yield change



How to produce iPETS scenario with climate effects on crop yields (i.e., land productivity)?

Aggregated land use



Crop map

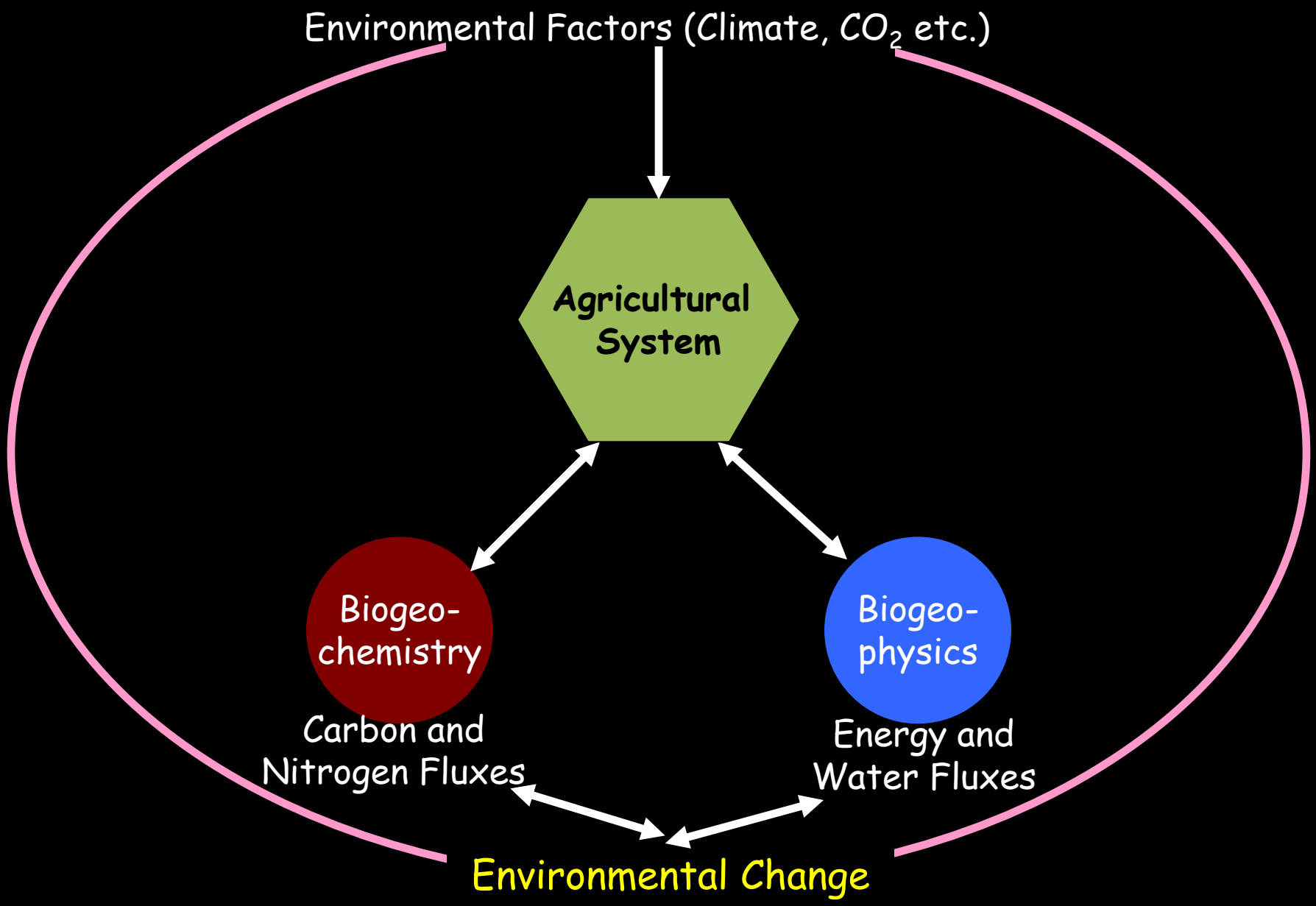
One option, but:

Need to run CESM, or at least CLM/ISAM , again for each iteration

No dynamic crops, pasture in CLM/ISAM

Evaluating the Crop Productivity under Variable and Changing Climate: An Integrated Data-Modeling Approach

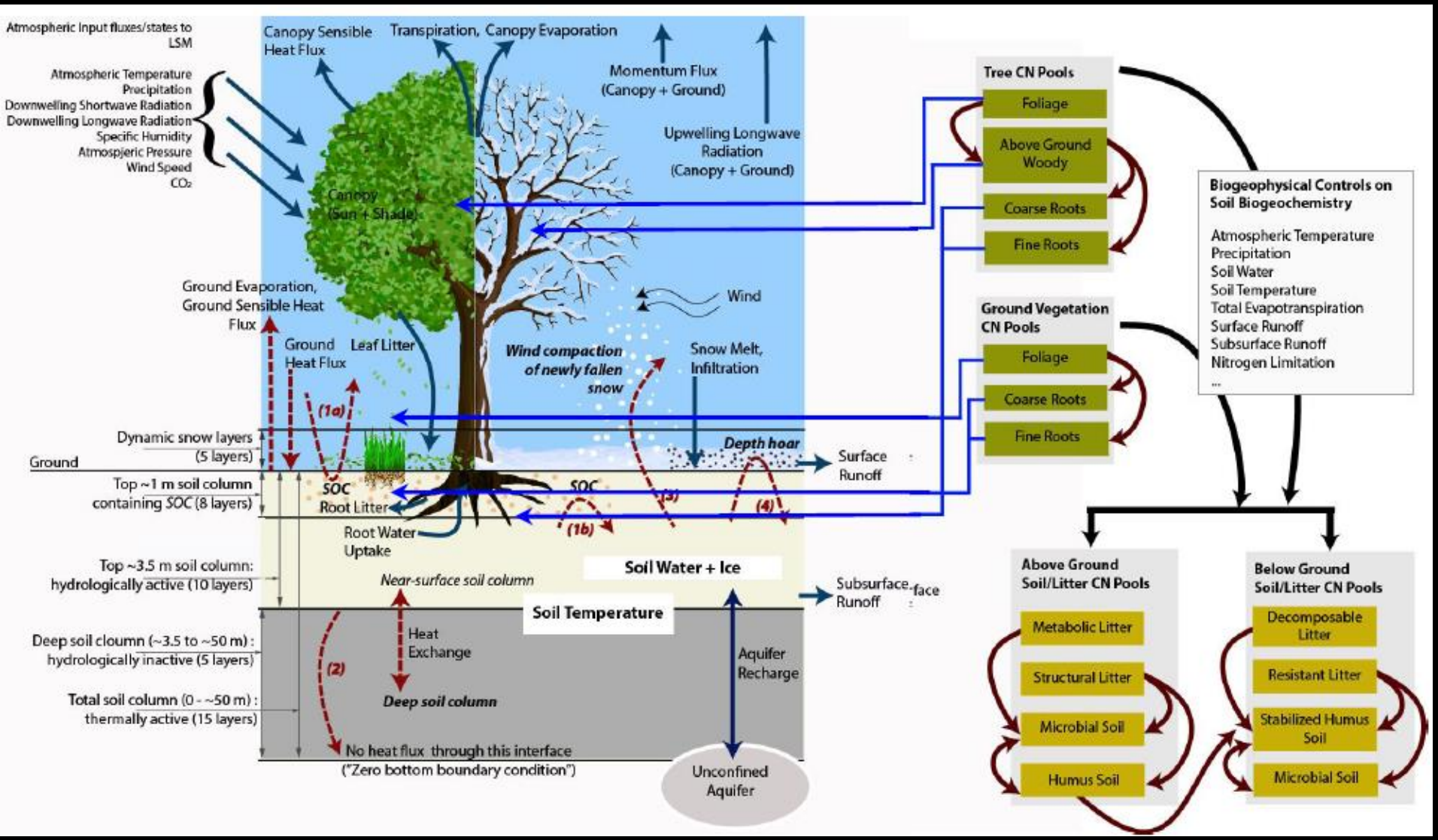
Interactions between Crops, Biogeophysics and Biogeochemistry



Overall Objective

- Understanding the fluxes of nutrients (C, N, P), energy and water between terrestrial ecosystems (including crops) and atmosphere require improved representation of *certain dynamic aspects of vegetation and soil processes*

Conceptual Diagram of ISAM



ISAM Land Surface Model

- **Biogeochemical Processes**
  - Coupled C and N dynamics (*Jain et al., 2009*)
  - Comprehensive above and below ground litter and SOM decompositions (*Yang et al., 2009*)
  - Land Cover and Land Use Change, including secondary forest dynamics (*Yang et al., 2010*)
- **Biophysical Processes**
  - Above-ground canopy biogeophysics **processes** (Barman et al, 2014a)
  - Originally, soil hydrology adapted from the NCAR **CLM3.5 (**Barman et al., 2014b).
  - Many Further **modifications** in biogeophysics, including recent advances in vegetation, soil, snow interactions (El-Masri et al., 2014)

Important Processes

- dynamic phenology and corresponding LAI schemes, which account for light, water, and nutrient stresses while allocating the assimilated carbon to leaf, root, stem and grain pools;
- dynamic vegetation structure growth, which better simulate the canopy height;
- dynamic root distribution processes in the soil layers, which better simulate the root response of soil water uptake and transpiration;
- processes controlling carbon turnover rates in soils that are regulated by species composition, allocation, litter decomposition, and fine root turnover

Phenology in Current Land Surface Models

Model name	Resolution	Leaf onset	Control on LAI	Leaf loss	Source
BEPS	Daily	Satellite	Satellite	Satellite	Ju *et al.* (2006)
Biome-BGC	Daily	GDD and radiation sum	Dynamic C allocation	Daylength and low temperature	Thornton *et al.* (2002)
Can-IBIS	Half-hourly	T threshold	GDD and dynamic C	Prescribed	El Maayar *et al.* (2002)
CN-CLASS	Half-hourly	C balance	C balance	Daylength and low temperature	Arain *et al.* (2006)
DLEM	Daily	$T_{7\text{-day}} >$ threshold	GDD to PFT limit	Daylength and low temperature	Tian *et al.* (2010)
Ecosys	Hourly	Hours above T threshold	Dynamic C allocation	Hours below T threshold	Grant *et al.* (2009)
ED2	Half-hourly	Semi-prescribed	Dynamic C allocation	GDD and leaf turnover	Medvigy *et al.* (2009)
ISAM	Half-hourly	Prescribed	Prescribed	Prescribed	Jain & Yang (2005)
LoTEC	Half-hourly	GDD	GDD	T-dependent turnover	Hanson *et al.* (2004)
LPJ_wsl	Daily	GDD	GDD	Leaf longevity (prescribed)	Sitch *et al.* (2003)
ORCHIDEE	Half-hourly	GDD and chilling	Dynamic C allocation	Decreasing T and T threshold	Krinner *et al.* (2005)
SiB3	Half-hourly	Prescribed	Prescribed	Prescribed	Baker *et al.* (2008)
SiBCASA	10 min	Prescribed	Prescribed	Prescribed	Schaefer *et al.* (2008)
SSiB2	Half-hourly	Prescribed	Prescribed	Prescribed	Zhan *et al.* (2003)

Richardson et al. (GCB, 18,566-584. 2012)

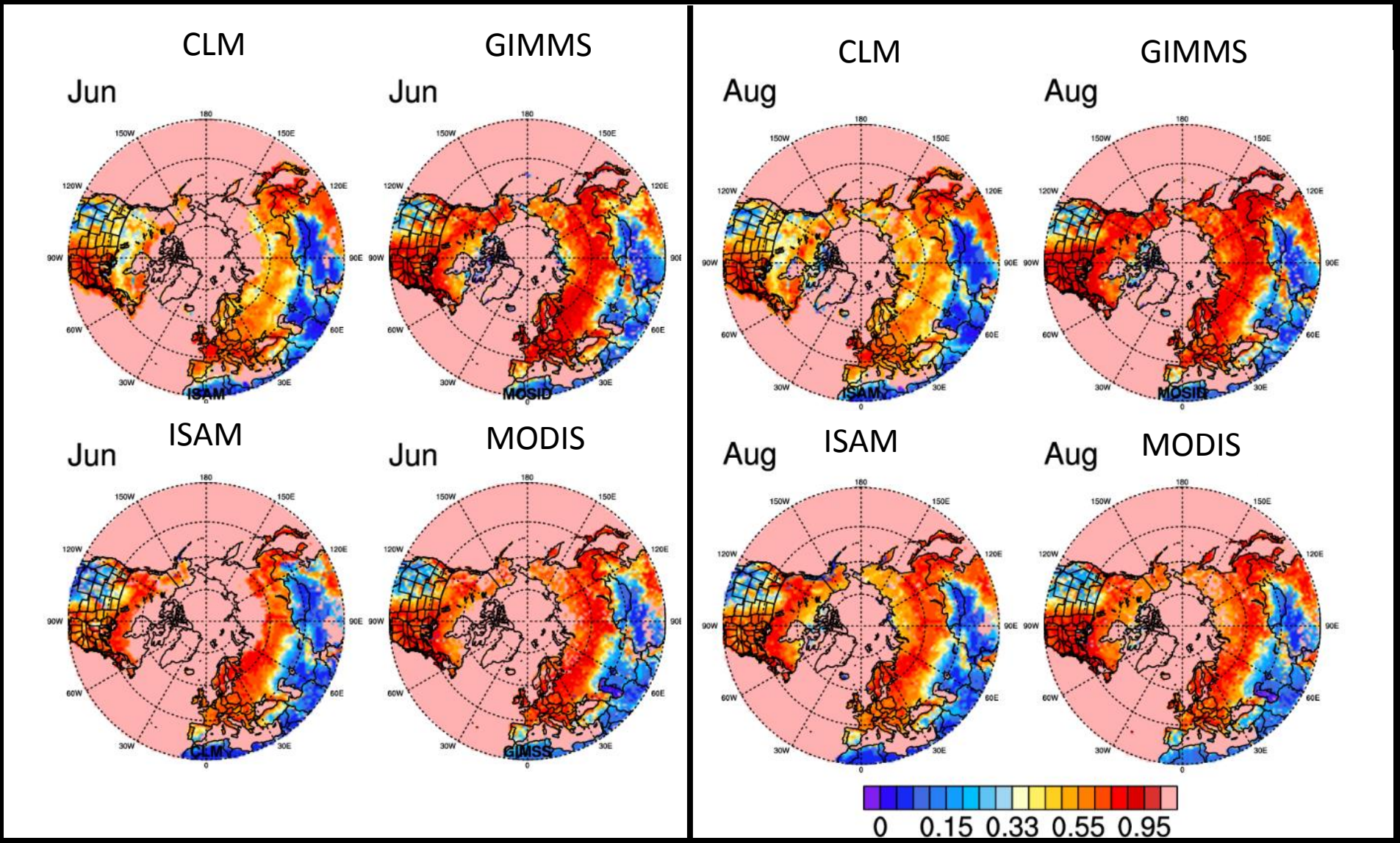
Phenology in Current Models

- Most global scale models use phenology formulations either based on GDD or prescribe phenology
  - Fixed leaf onset and offset based on growing degree days (GDD)
  - GDD controls LAI during the growing season
  - GDD and leaf turnover rate for leaf offset
  - Temperature dependent turnover
- GDD and prescribe approaches suffer from its ability to portray the LAI seasonality under current or even future climate change scenarios

Phenology in the Current Version of ISAM

- A carbon-gain-based (not temperature based)
  - Leaf onset when it is advantageous for plant to have leaves (or carbon assimilation)
  - Leaf offset when plant lose carbon under unfavorable environmental conditions
    - Shorter day length
    - Colder temperature
    - Soil moisture stress
- Robust and can be applied globally
- Perform acceptably for both current and future climatic conditions

Model and Data Based Estimates for Growing Seasons in the Northern Hemisphere



ISAM Accounts for Dynamic Root

- Change in root biomass results in change in root density with depth
- Root depth not prescribed but vary based on soil moisture availability
  - Under water stress conditions roots can grow much deeper and increase water uptake
  - Increase water uptake increases the growing season
  - Increase water uptake (or transpiration) increase LE and reduce water stress effect on GPP

Other Model Extensions and Significance

- Agriculture practices simulation
  - -Dynamic planting and harvest scheme: better simulate varied planting and harvest time across diverse environmental conditions.
  - -Progressive nitrogen fertilizer scheme: better simulate the impact of N fertilizer on soil N dynamics
- Parameterization of bedrock depth based on realistic bedrock depth data
  - –better simulate total soil water storage and its spatial and temporal variation.
- Parameterization of the effect of soil structure on soil hydraulic conductivity
  - –better simulate soil water infiltration in the fine-textured soil

Biogeosciences, 10, 8039–8066, 2013
www.biogeosciences.net/10/8039/2013/
doi:10.5194/bg-10-8039-2013
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Biogeosciences
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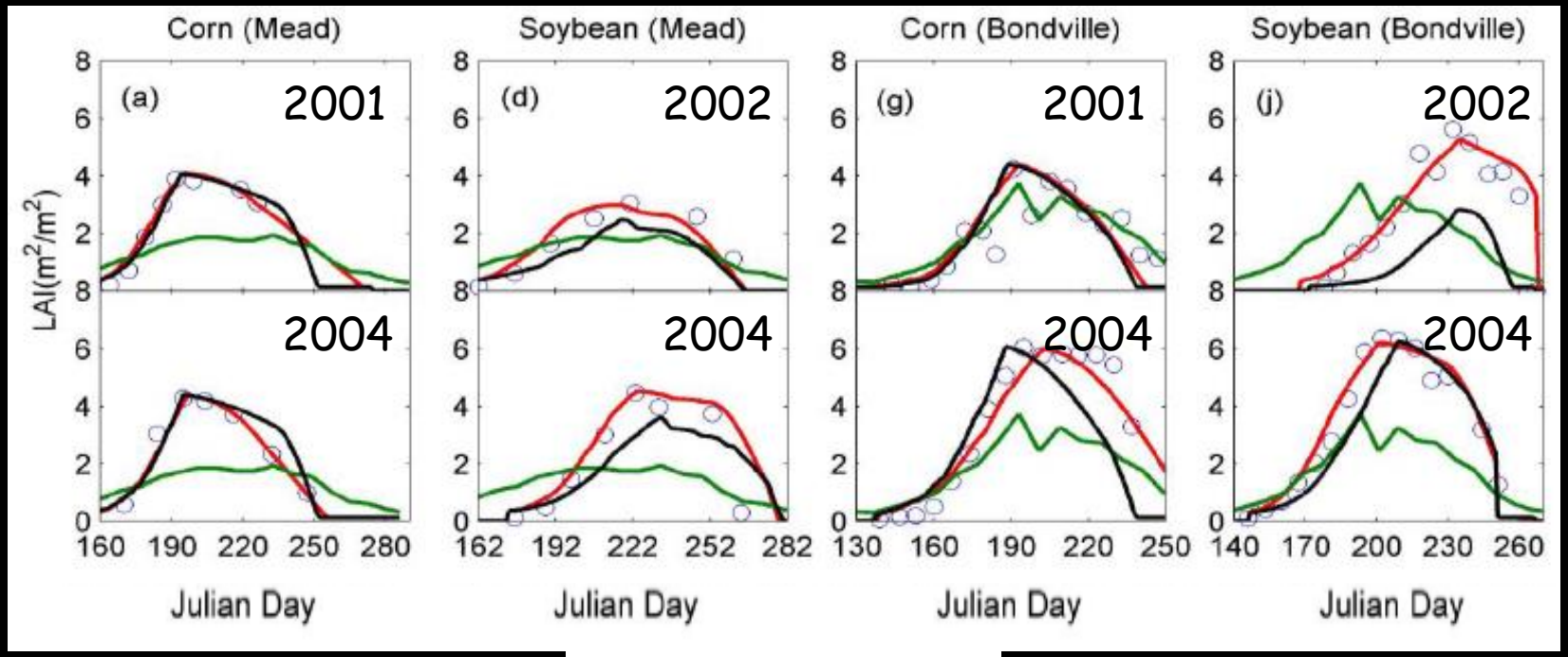
Implementation of dynamic crop growth processes into a land surface model: evaluation of energy, water and carbon fluxes under corn and soybean rotation

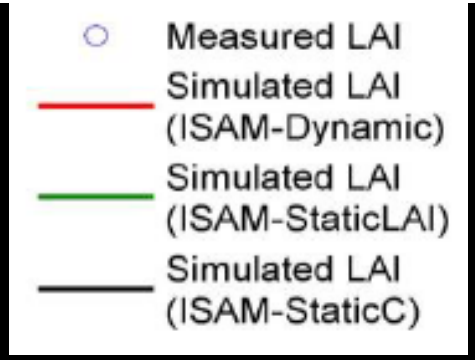
Y. Song[1], A. K. Jain[1], and G. F. McIsaac[2]

ISAM Approach

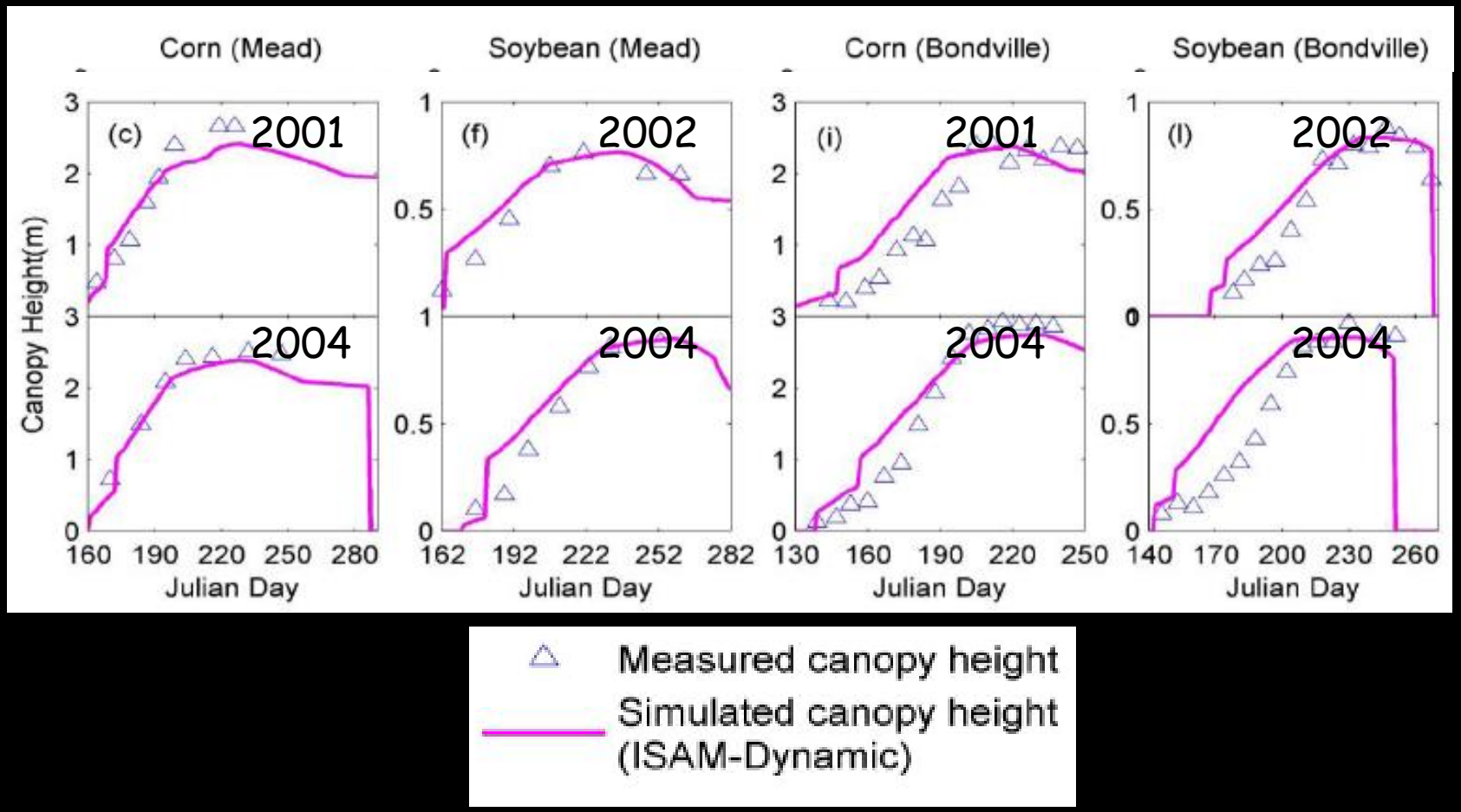
- Estimates crop yield at
  - Site level at diurnal scale
  - Site level at daily scale
  - Regional level at diurnal scale
  - Global scale at daily, yearly and decadel scales

Model vs. Measured LAI for Corn and Soy (2001- 2004)

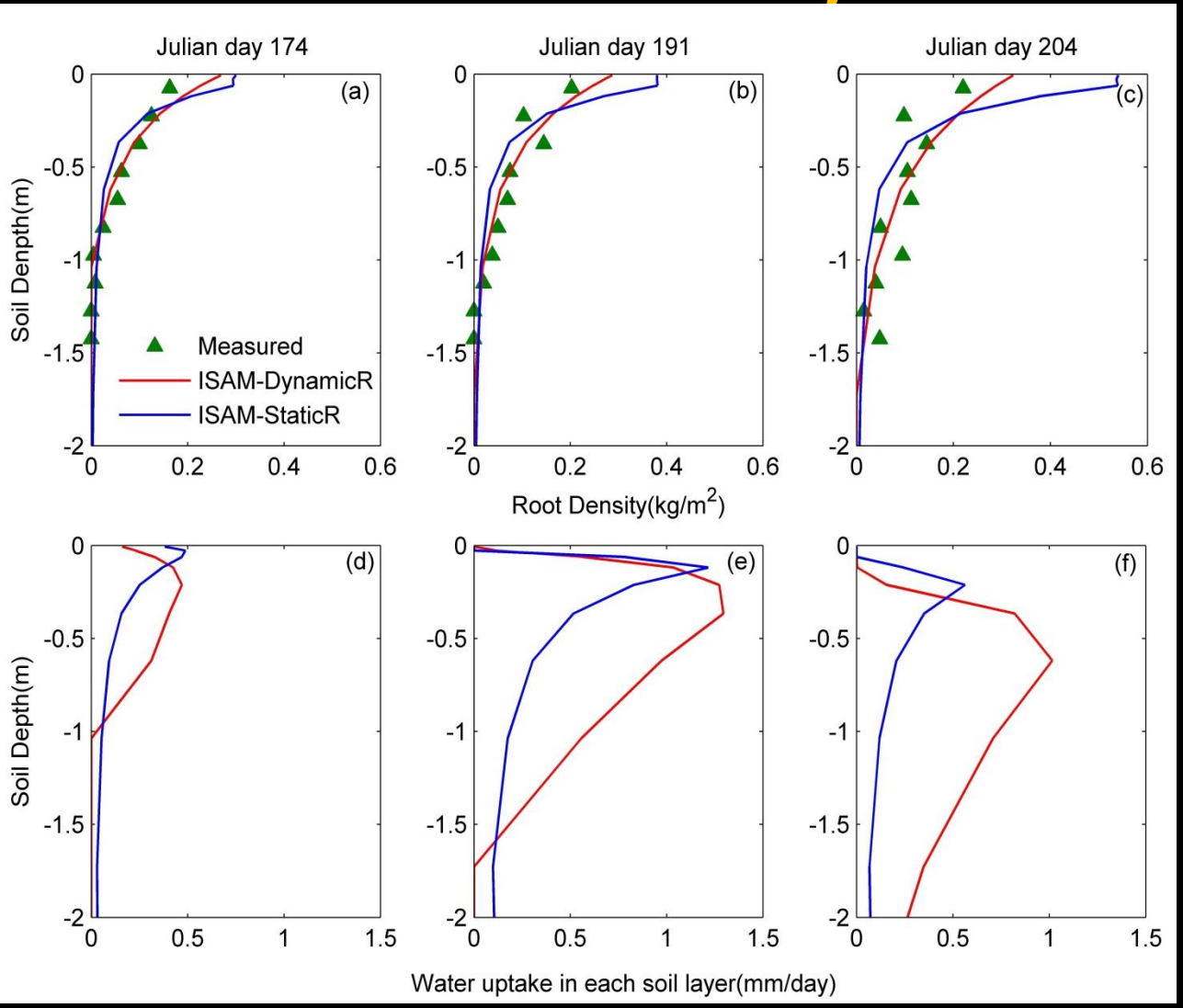




Model vs. Measured LAI for Corn and Soy (2001- 2004)



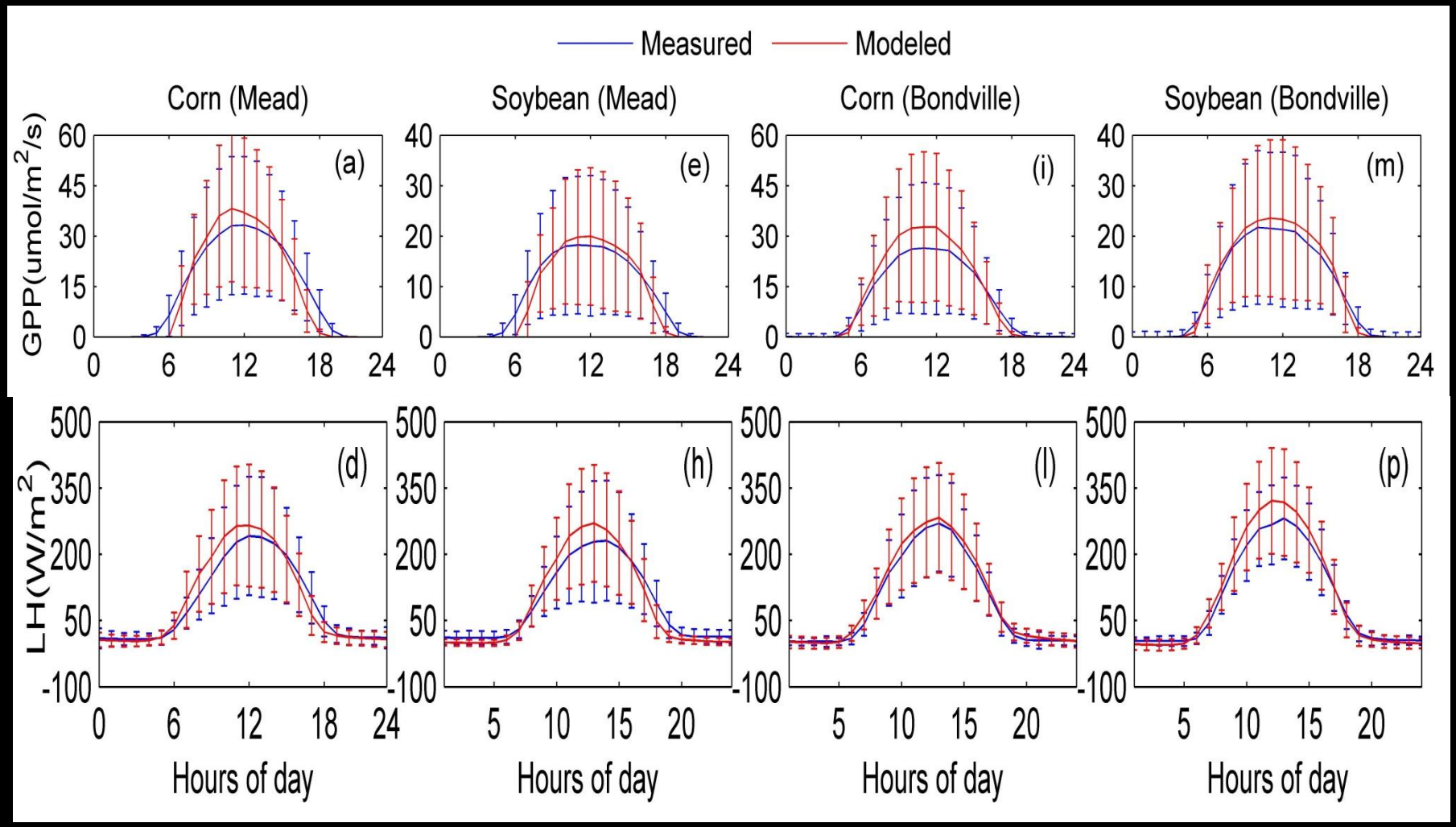
Comparison of modeled and measured corn root density and water uptake



Root grows deeper soil layers under water stress conditions.

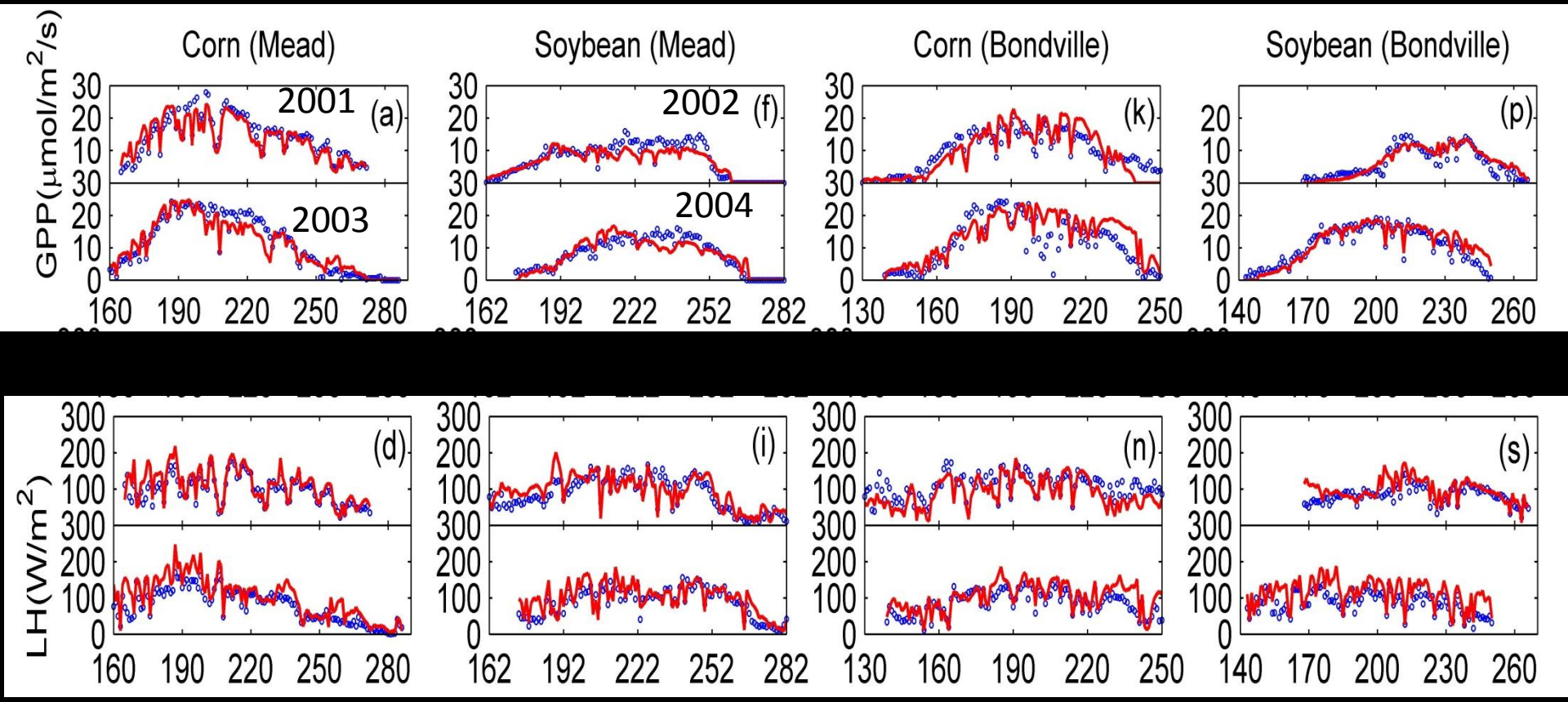
Root extracts more water from deeper soil layers, instead of shallow soil layer, leading to redistribution of water among soil layers.

Measured and Modeled Mean Hourly GPP & LH 2001-2004 Growing Period



Yang et al. (Biogeosciences, 2013)

Measured and Modeled Mean Hourly GPP & LH 2001-2004 Growing Period

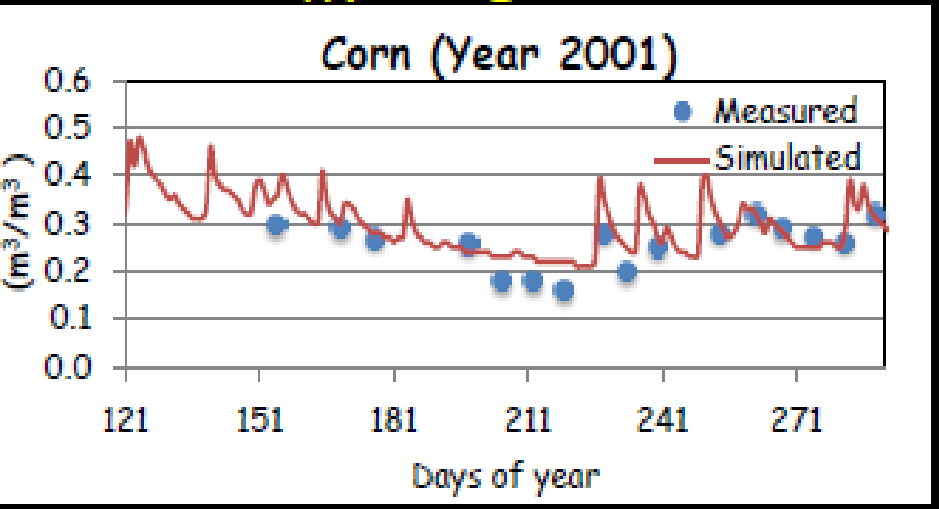


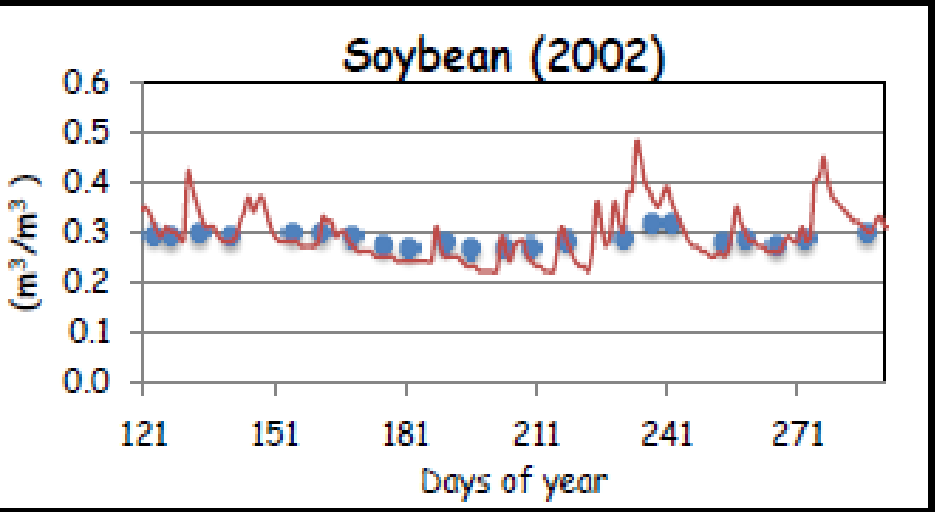
The top panels for 2001 and 2002 growing seasons for corn and soybean; whereas the bottom panels are for 2003 and 2004

Yang et al. (Biogeosciences, 2013)

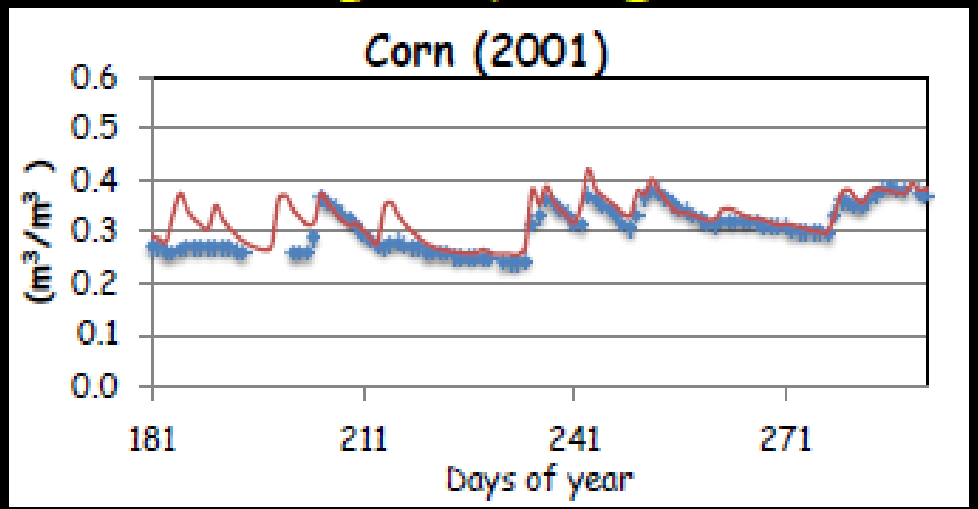
Measured and Simulated Soil Water Content

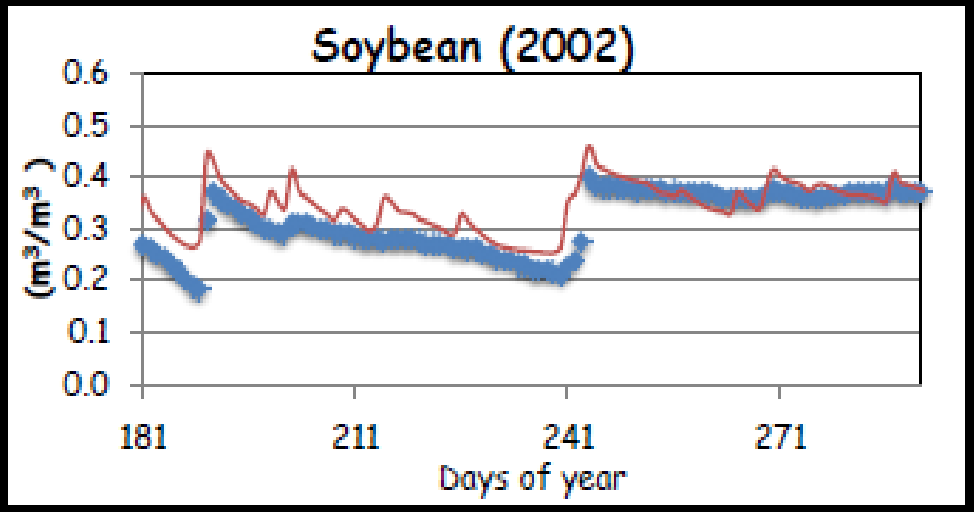
Mead Site



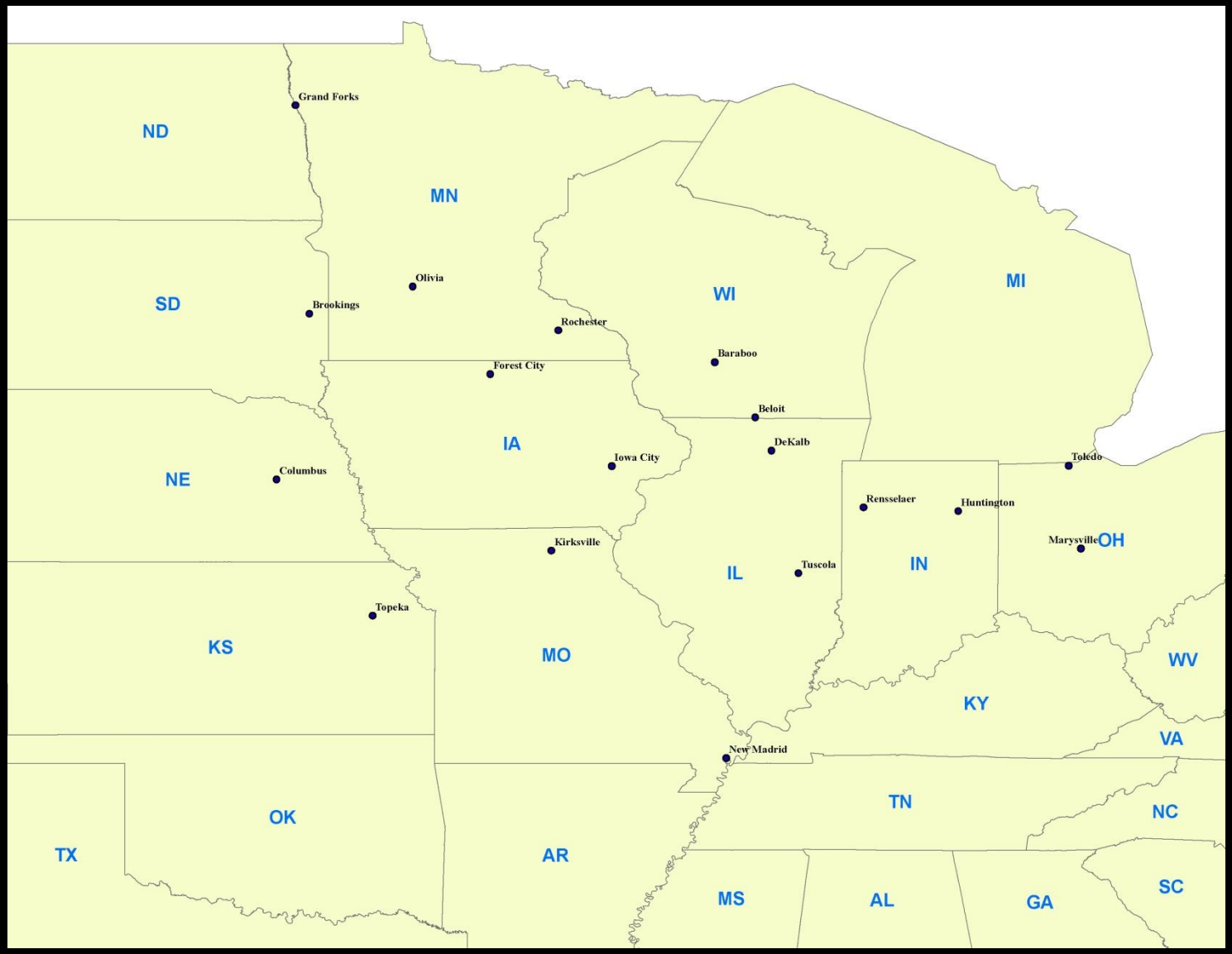


Bondville Site

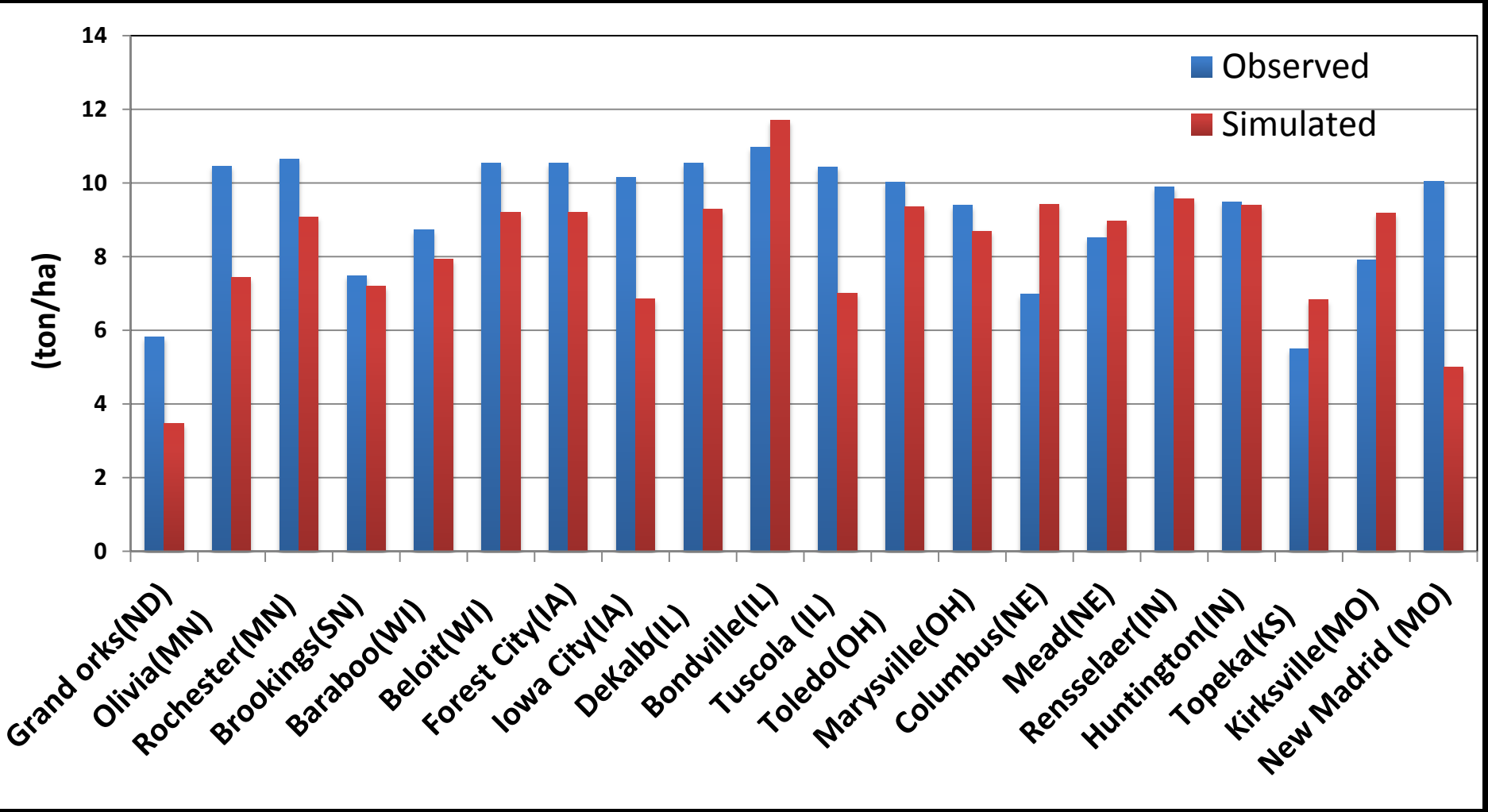




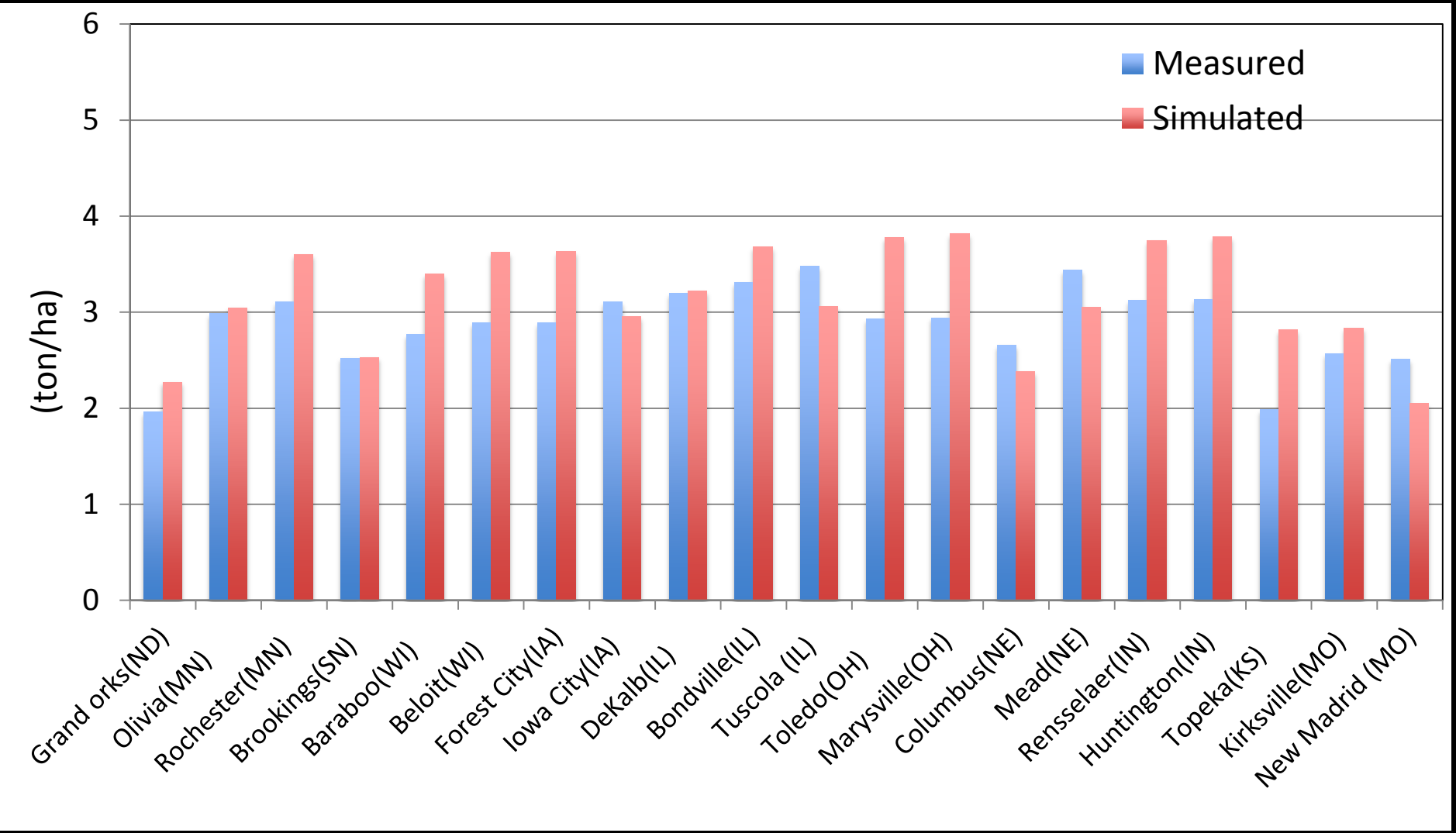
NASS 18 Sites Distribution



Corn Yield
Average for 2000-2010



Soybean Yield
Average for 2000-2010



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10.1002/2015GL063841

Key Points:

- In Corn Belt, El Niño (La Niña) has positive (negative) impact on corn yield
- Crop models can capture the regional impacts of ENSO on yield
- The study highlights the advantage of simpler crop models and gridded data sets

Supporting Information:

- Figures S1–S4 and Tables S1 and S2

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Citation:
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Crop models capture the impacts of climate variability on corn yield

Dev Niyogi[1,2], Xing Liu[1], Jeff Andresen[3], Yang Song[4], Atul K. Jain[4], Olivia Kellner[2], Eugene S. Takle[5], and Otto C. Doering[6]

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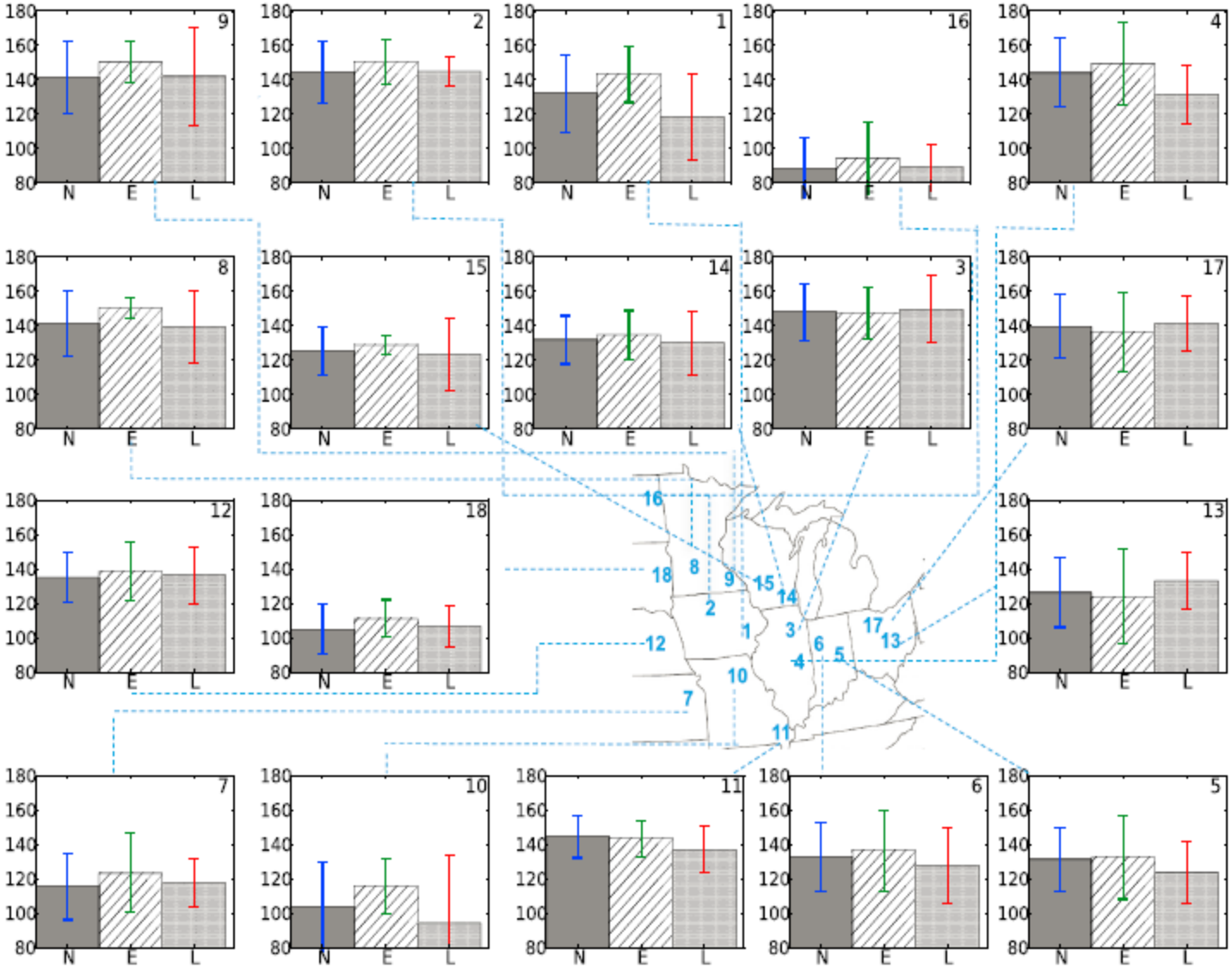
Abstract We investigate the ability of three different crop models of varying complexity for capturing El Niño–Southern Oscillation-based climate variability impacts on the U.S. Corn Belt (1981–2010). Results indicate that crop models, irrespective of their complexity, are able to capture the impacts of climate variability on yield. Multiple-model ensemble analysis provides best results. There was no significant difference between using on-site and gridded meteorological data sets to drive the models. These results highlight the ability of using simpler crop models and gridded regional data sets for crop-climate assessments.



1. Johnson, IA 2. Winnebago, IA 3. DeKalb, IL 4. Douglass, IL 5. Huntington, IN 6. Jasper, IN
7. Shawnee, KS 8. Olmsted, MN 9. Renville, MN 10. Adair, MO 11. New Madrid, MO 12. Platte, NE
13. Union, OH 14. Rock, WI 15. Sauk, WI 16. Grand Forks, ND 17. Lucas, OH 18. Brookings, SD

Figure 1. Research domain (the U.S. Corn Belt) and bar charts with error bars of corn yield under ENSO events for selected 18 counties used in model assessment. (N: normal, E: El Niño, and L: La Niña. *Y* axis represents corn yield in bu/acre.)

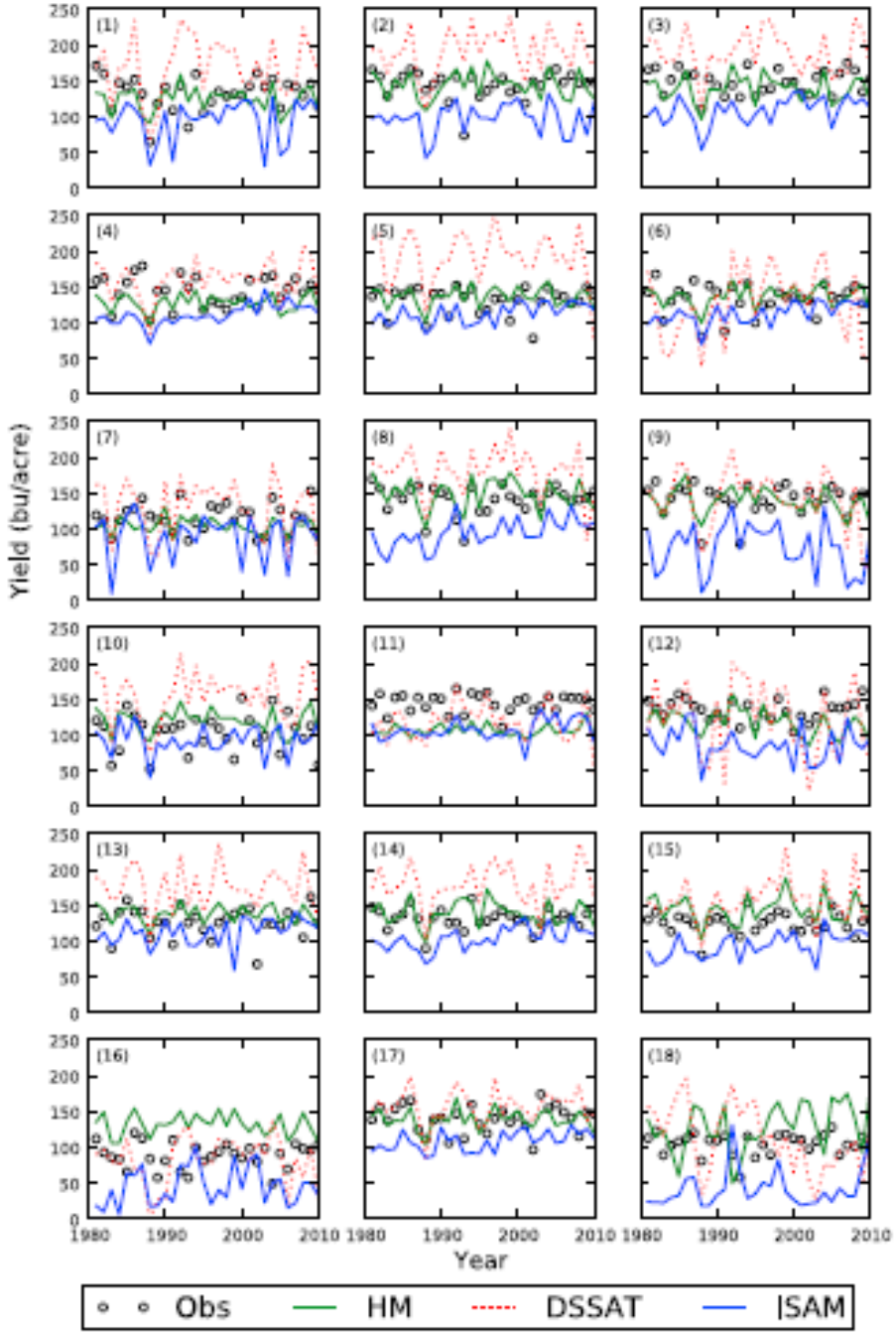


Figure 3. Comparisons of three models (Hybrid-Maize, DSSAT, and ISAM) using the gridded reanalysis meteorological data sets. Numbers (1–18) indicate locations as shown in Figure 1.

Table 1. Simulated Average Corn Yield (1981–2013) of 18 Counties Grouped Into ENSO Phases[a]

		Yield Ratio									
		HM_S		HM_R		$DSSAT_S$		$DSSAT_R$		$ISAM_R$	
No.	County	E/N	L/N	E/N	L/N	E/N	L/N	E/N	L/N	E/N	L/N
1	Johnson, IA	1.03	0.96	1.04	0.97	1.08	0.96	1.11	0.92	1.03	1.07
2	Winnebago, IA	1.02	0.97	1.04	0.94	1.05	1.14	1.07	0.95	1.04	1.05
3	DeKalb, IL	1.05	0.94	1.06	0.95	1.05	1.05	1.09	0.92	1.01	1.03
4	Douglass, IL	1.00	0.96	1.01	0.98	1.06	0.92	1.05	0.92	0.98	0.96
5	Huntington, IN	1.04	0.93	1.04	0.95	1.02	0.94	1.09	0.87	0.98	1.03
6	Jasper, IN	1.05	0.94	1.03	0.95	0.91	0.77	0.99	0.84	0.98	1.00
7	Shawnee, KS	1.03	0.93	0.98	0.97	1.06	0.91	1.06	0.94	1.09	0.93
8	Olmsted, MN	1.02	1.02	1.05	0.98	1.16	1.00	0.99	0.98	1.00	1.03
9	Renville, MN	1.00	0.97	1.07	0.94	1.20	0.98	1.07	0.84	1.13	0.96
10	Adair, MO	1.08	0.94	1.04	0.96	1.20	0.94	1.08	0.92	1.09	0.97
11	New Madrid, MO	0.99	0.94	1.01	0.95	1.03	0.99	1.04	0.88	1.01	0.94
12	Platte, NE	1.04	1.00	0.98	0.97	0.97	0.91	0.93	0.92	1.04	0.86
13	Union, OH	1.04	0.96	1.02	0.95	1.04	0.94	1.05	0.91	1.00	0.96
14	Rock, WI	1.02	0.94	1.05	0.94	1.07	0.95	1.11	0.95	0.99	1.04
15	Sauk, WI	1.01	1.01	1.06	1.02	1.05	1.07	1.03	1.01	1.03	1.10
16	Grand Forks, ND	0.91	1.01	1.06	0.98	1.24	1.01	1.20	0.90	1.10	1.00
17	Lucas, OH	1.03	0.96	1.03	0.95	0.98	0.90	1.05	0.93	1.00	1.04
18	Brookings, SD	1.01	1.06	1.01	1.06	0.93	0.73	1.00	0.90	1.05	1.21
	Average	1.02	0.97	1.03	0.97	1.06	0.95	1.06	0.92	1.03	1.01(0.99[b])

[a] *S*: model running with on-site meteorological data; *R*: model running with reanalysis meteorological data; E: El Niño; L: La Niña; and N: normal. Event to event variability is available in the supporting information Figure S4.
[b] Average without using Brookings, SD.

The Impact of Climate Change on Production of Multiple Food Crops in the 21st Century-An Analysis based on Two Land Surface Models

Input Data

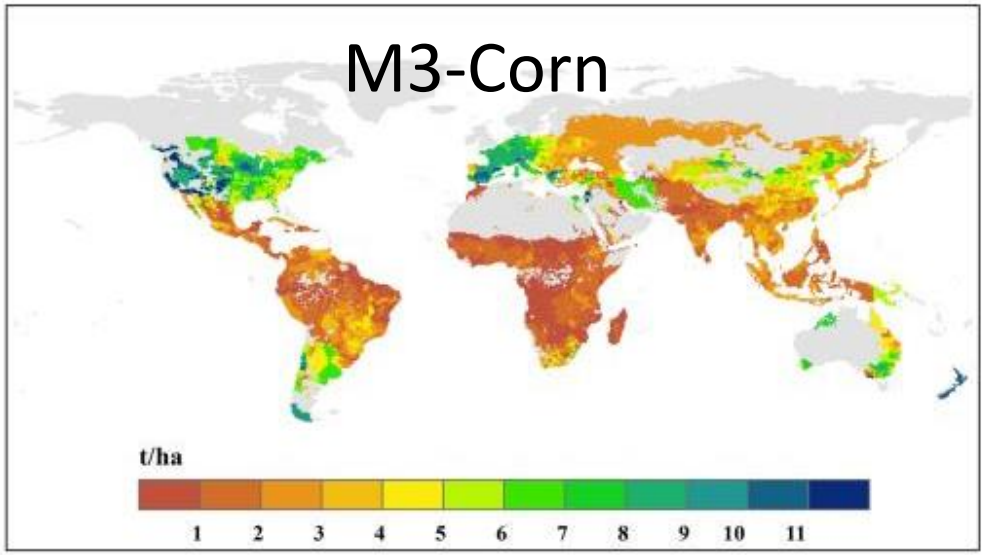
- **Climate Data**: Climate forcing date for the historical time 1901- 2005 and for the future climate scenario CMIP5 RCP8.5 for the time period 2006-2100 based on CESM (CLM 4.5).
- **Crops Area Data**: Monfreda et al. (2008) cropping system dataset (M3 data)

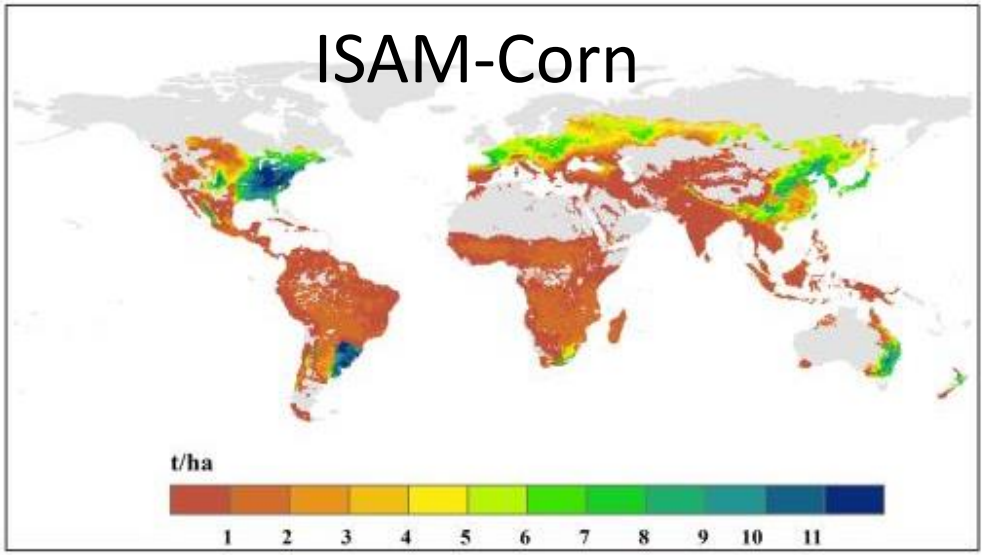
Experiments Performed

Three experiments are performed for Using ISAM and CLM LSMs over the time period 1901-2100

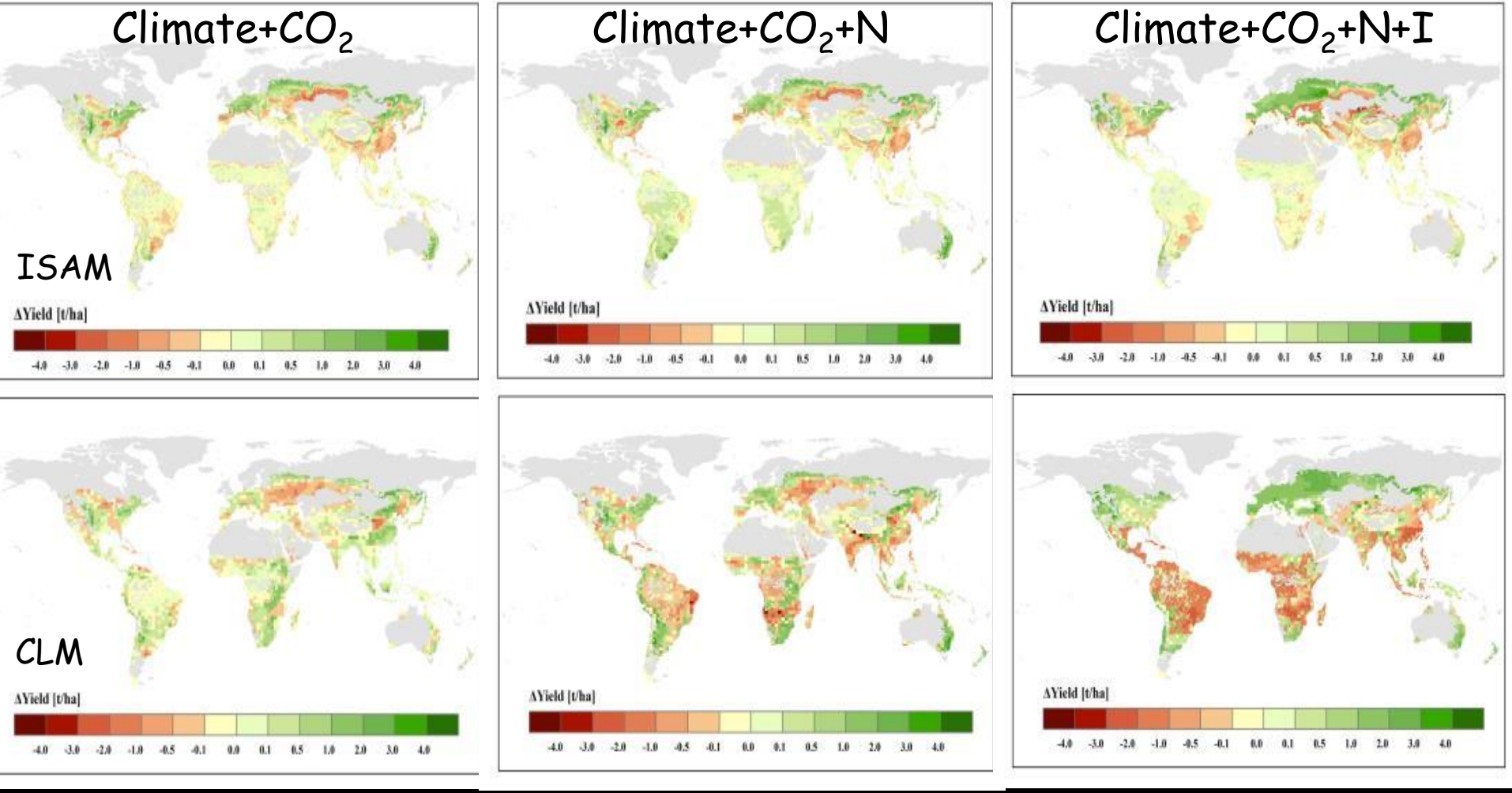
- Climate+CO_2 case: the model is driven by temporally varied climate forcing and atmospheric CO_2 concentration.
- Climate+CO_2+N case: the model is driven by varied climate forcing and atmospheric CO_2 concentration and with interactive N fertilization for crops.
- Climate+CO_2+N+I case: the model is driven by varied climate forcing and atmospheric CO2 concentration and with interactive N fertilization and Irrigation for crops

Comparison of Mean Crop Yield over the Period 1997-2003 between ISAM and M3 Data

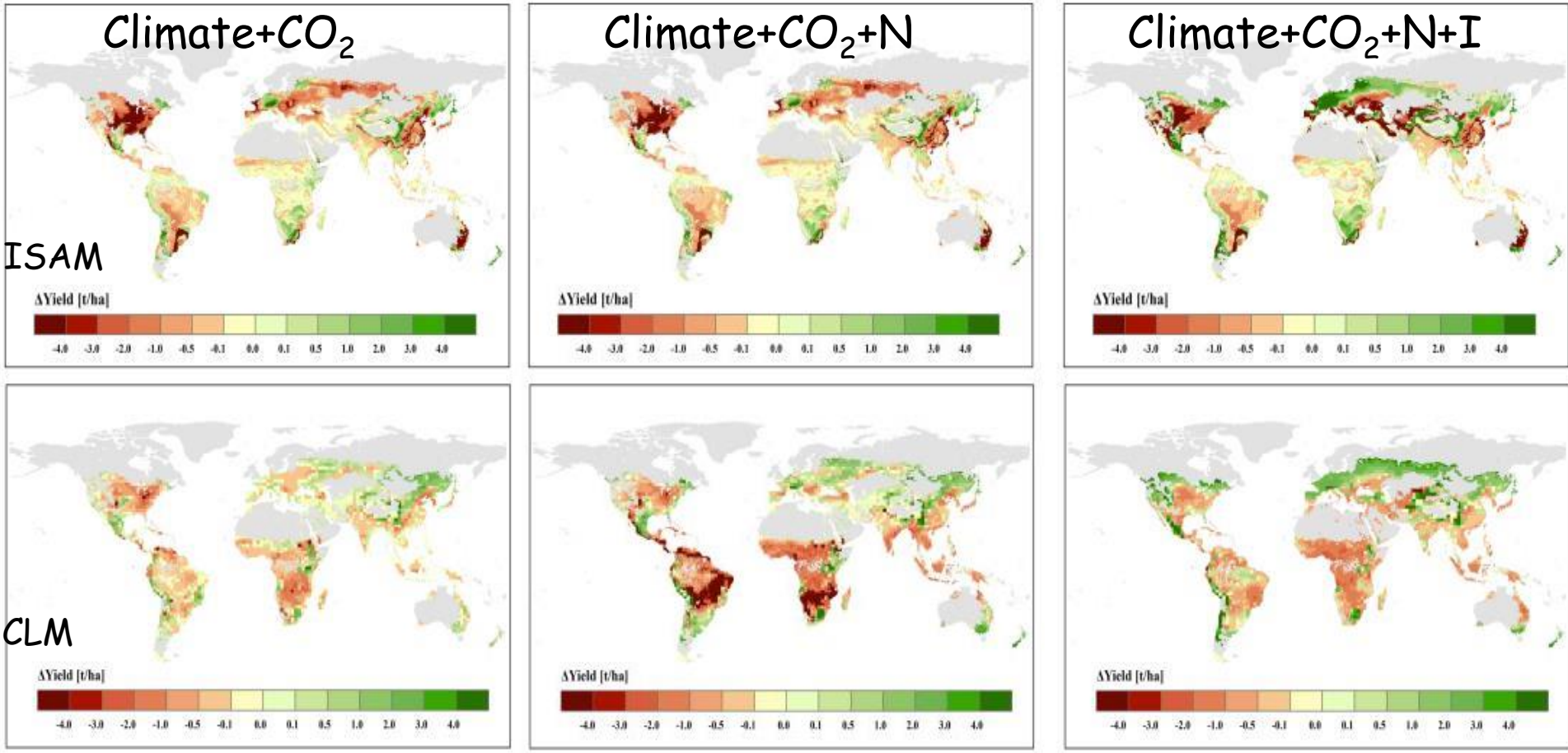




Change in Historical Corn Yield (2000s -1960s)



Change in Future Corn Yield (2090s -2000s)



Thank you