

Estimating global warming potential for agricultural landscapes with minimal field data and cost

Working Paper No. 142

CGIAR Research Program on Climate Change,
Agriculture and Food Security (CCAFS)

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Gopal Datt Bhatta
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Eva Wollenberg



RESEARCH PROGRAM ON
**Climate Change,
Agriculture and
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Abstract

Greenhouse gas (GHG) emissions from agriculture comprise 10-12% of anthropogenic global emissions; and 76% of the agricultural emissions are generated in the developing world.

Landscape GHG accounting is an effective way to efficiently develop baseline emissions and appropriate mitigation approaches. In a 9,736-hectare case study area dominated by rice and wheat in the Karnal district of Haryana state, India, the authors used a low-cost landscape agricultural GHG accounting method with limited fieldwork, remote sensing, and biogeochemical modeling. We used the DeNitrification-DeComposition (DNDC) model software to simulate crop growth and carbon and nitrogen cycling to estimate net GHG emissions, with information based on the mapping of cropping patterns over time using multi-resolution and multi-temporal optical remote sensing imagery. We estimated a mean net emission of 78,620 tCO₂e/yr (tons of carbon dioxide equivalents per year) with a 95% confidence interval of 51,212-106,028 tCO₂e/yr based on uncertainties in our crop mapping and soil data. A modeling sensitivity analysis showed soil clay fraction, soil organic carbon fraction, soil density, and nitrogen amendments to be among the most sensitive factors, and therefore critical to capture in field surveys. We recommend a multi-phase approach to increase efficiency and reduce cost in GHG accounting. Field campaigns and aspects of remote sensing image characteristics can be optimized for targeted landscapes through solid background research. An appropriate modeling approach can be selected based on crop and soil characteristics. Soil data in developing world landscapes remain a significant source of uncertainty for studies like these and should remain a key research and data development effort.

Keywords

Greenhouse gas accounting; Biogeochemical modeling; Remote sensing; Geographic Information Systems; Low emissions development; Climate change mitigation

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Acronyms

C	Carbon
CCAFS	CGIAR Research Program on Climate Change, Agriculture and Food Security
CH ₄	Methane
CO ₂ e/ha	carbon dioxide equivalent per hectare
DNDC	De-Nitrification-De-Composition model
dSOC	Soil organic carbon sequestration rate
GHG	Greenhouse gas
HWSD	Harmonized World Soils Database
IPCC	Intergovernmental Panel on Climate Change
N	Nitrogen
N ₂ O	Nitrous oxide
NDVI	Normalized Difference Vegetation Index
PBM	Process-Based Biogeochemical Models
SAR	Synthetic aperture radar
SOC	Soil organic carbon
TDD	Total degree days
UNFCCC	United Nations Framework Convention on Climate Change

1. Introduction

The global agricultural sector contributes 10-12% to annual anthropogenic greenhouse gas (GHG) emissions (Metz et al. 2007), and 76% of agricultural emissions are generated in the developing world, defined as Non-annex 1 countries under the United Nations Framework Convention on Climate Change (UNFCCC) (WRI 2014). Emissions measurement and accounting are necessary to develop appropriate GHG mitigation practices; landscape-level GHG accounting offers particular advantages in that landscape-level accounting assesses a specifically defined geographic area and reports on a defined set of emissions (Walker et al. 2014). Landscape accounting is advantageous both in terms of reducing relative costs and assessing the ecological flows from one part of a landscape to another (Milne et al. 2013).

Significant challenges to acquiring the necessary data for GHG accounting currently exist in the developing world. Precise data on emissions are often lacking or of poor spatial resolution; collection of field data, particularly GHG emissions data, tends to be expensive and time consuming. Intergovernmental Panel on Climate Change (IPCC) emission factors can be used, but they often have significant associated uncertainty, such as stated uncertainty ranges and the applicability of factors, which may not have been developed for the landscape in question. As an alternative, process-based biogeochemical models (PBMs) provide an inexpensive way to estimate agricultural emissions and crop yields, particularly when combined with field data (on crop management and spatial patterns), ancillary inputs data (e.g. climate and soils), and crop maps based on remote sensing. PBMs can also evaluate mitigation options without performing costly additional field experiments.

In this paper, we describe an approach to landscape-level GHG estimation using a combination of limited field work and mapping of agricultural systems via remote sensing. We use freely available data in combination with a freely available process-based biogeochemical model. While it has been argued that field measurement of GHG emissions is necessary for the success of landscape-level accounting (Milne et al. 2013) and we do not disagree, the reality is that field measurements are cost-prohibitive for many quantification efforts.

In this study, we used a robust and well-parameterized agro-ecological model, the De-Nitrification-De-Composition model (DNDC) (Li and Frolking 1992, Li et al., 1994, Li 2001; DNDC 2014 available online at <http://www.dndc.sr.unh.edu>). We provide a case-study in a developing-world landscape dominated by smallholder agriculture. For illustrative purposes, we include a model sensitivity analysis to demonstrate how field data collection could be targeted. In addition, we provide recommendations for future work based on lessons learned at our case study site and others like it.

2. Case Study: Greenhouse gas accounting in Karnal, India

This case study illustrates our approach to combining field work, remote sensing, and biogeochemical modeling for GHG quantification. The Karnal, India site is approximately an 11.5km x 11.5km region (~9,736 hectares), centered at latitude 29.80 and longitude 76.94. Soils are loamy with moderate clay and organic matter content. The principal summer crop (July-October) is rice. The principal autumn-winter crop (November-April) is wheat. Other autumn-winter crops include berseem clover, mustard, and vegetables (all of which are grown in rotation with rice). The spring season is usually fallow, though sometimes vegetables are planted.

2.1. Methods

2.1.1. Field data

Field data collection informed both GHG simulations and remote sensing work. Crop management data and locational data on crop rotations were collected for both image calibration and validation. Our field data collection consisted of *a priori*, off-site expert interviews and documents review, expert (farmer) on-site interviews, sampling scheme development, and photographic sampling. Field work occurred February 15-18, 2013.

We utilized information from Karnal household surveys (Singh 2013), in coordination with agronomists (for example, through personal communications with M.L. Jat of the International Maize and Wheat Improvement Center, CIMMYT), and interviews with local experts (knowledgeable farmers). We surveyed 50 farmers with relatively large farms (>0.5 ha) across 21 villages, to account for geographic heterogeneity. We stratified our selection of

farmers by existing crop rotation category, approximately as follows: 70% rice-wheat, 20% rice-non-wheat, 10% vegetables and other non-rice crops. From each farmer, we collected crop management and yield information (crop types, plant and harvest dates, fertilizer and organic amendment applications, and tillage regimes). Since crop management variability was low, we created a consistent set of crop management parameters augmented using ancillary data (Department of Agriculture and Cooperation 2013, IRRI 2013, Gathala et al. 2013). Crop management was verified via expert review (personal communication with P.K. Aggarwal of CCAFS).

Based on information from local experts, we selected ground truth points from which to collect photographs. We took 96 photographs of relatively homogeneous fields across all rotation types (continuous rice-wheat, rice-non-wheat, and other non-rice crops).

2.1.2. GHG simulations

DNDC was used to simulate crop growth and yield, carbon (C) and nitrogen (N) cycling, N leaching, and GHG emissions for the predominant rotations (rice-wheat, rice-mustard, rice-berseem, rice-vegetables). Emissions were calculated for the cropping years 2010-2012.

We ran DNDC for an 18 years-simulation to ensure that soil organic carbon (SOC) pools were in approximate equilibrium. The first 15 years were the SOC initialization phase (1995-2009). The last three years allowed for and captured climatic variability and were the summary timeframe (2010-2012). We assumed consistent management throughout the 18-year time period.

Daily meteorological data (maximum and minimum temperature in °C and precipitation in centimeters for 1995 through 2012) were derived from the NASA Modern Era Retrospective-Analysis for Research and Applications dataset (MERRA), extracted from the University of New Hampshire Earth Systems Atlas website (NASA 2010). To estimate nitrogen deposition, we used data from the Oak Ridge National Laboratory Distributed Active Archive Center for Biogeochemical Dynamics. To derive mean N deposition for this site, we calculated a year-weighted average from the Global Maps of Atmospheric Deposition datasets (1993 estimated and 2050 predicted; Dentener 2006) to derive a 2010-2012 average.

Soil characteristics were extracted from the Harmonized World Soils Database (HWSD; FAO/IIASA/ISRIC/ISSCAS/JRC 2009). We used top-soil attributes for clay fraction (a proxy

for soil texture), bulk density, soil organic carbon fraction, and pH. HWSO is effectively geographic information systems (GIS) polygon data. Within each soil polygon, there are one or more soil types (HWSO ID)—the fraction of each soil type within each polygon is reported, however, the specific location of each soil type is not reported. We used soil types as the base modeling unit for this simulation. Model outputs were aggregated via area-weighting of soil types.

Crop management information was provided by CCAFS staff (Gopal Bhatta, Pramod Aggarwal personal communication) and integrated into a database processed via DNDC. To simulate biomass production accurately, DNDC requires precise calibration of all crop parameters. We used an iterative process to calibrate crop timing (duration to maturity), water requirements, and yield. Duration to crop maturity is based on total degree days (TDD) from the planting date. Degree days, as used by DNDC, accumulate on any day where the mean temperature meets or exceeds 10°C (i.e. a day with a mean temperature of 11°C would have 11 degree days). To estimate the TDD parameter, we calculated the sum of degree days between plant date and maturity date; we assumed that most producers harvested shortly after grain maturity and so set maturity dates to one week prior to harvest date (or drainage date in the case of rice). We selected the minimum TDD value over the 2010-2012 period to allow the crop to mature in all years.

We next calibrated crop growth based on mean yield as reported by CCAFS staff (Gopal Bhatta, unpublished data). We set the maximum biomass parameter based on mean reported grain yield, corrected for standard moisture content, and carbon content of 40% in all cases (Changsheng Li, personal communication). We simulated crop growth using actual fertilizer amounts and actual irrigation. Using this approach, modeled mean-annual yields were within 10% of reported yields.

We also calculated indirect (downstream) nitrous oxide (N₂O) emissions using IPCC emission factors (Nevinson 2000) and DNDC-modeled leaching and ammonia and nitric oxide emissions as:

$$N_2O_i = ((NH_3 + NO) * 0.01) + (N_{leach} * 0.015)$$

We calculated total N₂O emissions as direct plus indirect emissions:

$$N_2O_t = N_2O_d + N_2O_i$$

For each of the above, we calculated a three-year annual mean based on the results from 2010, 2011 and 2012.

Global warming potential (GWP) was calculated using IPCC factors (Forster et al., 2007) as follows:

$$\text{dSOC}_{\text{gwp}} = \text{dSOC} * -1.0 * 44.0 / 12.0 \text{ where dSOC is the SOC sequestration rate}$$

$$\text{CH}_4_{\text{gwp}} = \text{CH}_4 * 16.0 / 12.0 * 21.0$$

$$\text{N}_2\text{O}_{\text{gwp}} = \text{N}_2\text{O} * 44.0 / 28.0 * 310.0$$

The overall global warming potential rate was calculated as:

$$\text{GWP} = \text{dSOC}_{\text{gwp}} + \text{CH}_4_{\text{gwp}} + \text{N}_2\text{O}_{\text{gwp}}$$

For each site, to derive a single set of rates for each attribute, we calculated the following:

$$\text{rateawm} = \sum \text{rate}_i * \text{weight}_i$$

where,

rateawm = the area-weighted mean rate

rate_i = ith rate in a set of rates

weight_i = ith weight in a corresponding set of area-weights, calculated as:

soil polygon fraction of site * soil type fraction of polygon

2.1.3. Remote sensing

In Karnal, the objective of the remote sensing was to map the different crop rotations (e.g., winter wheat, fallow in spring, summer rice) for the area. It was important to use imagery from as few cropping years as possible to minimize the errors due to land use changes (such as urban development, changes in crop rotations). The seasonal crop maps were combined into crop rotation maps that were used to calculate total GHG emissions.

Based on the field surveys and crop management information, we classified the study region into as many different types of crop rotations classes as was possible with the imagery. Using atmospherically corrected surface reflectance (using the 6S atmospheric model) of the resulting clusters in combination with information from field photos, all pixels within a

cluster were assigned to a land-use class (i.e., wheat, berseem clover, mustard, vegetables, rice) depending on the season.

The crop year was divided into three seasons and appropriately timed satellite data were identified to provide information about the crop types during that period. Algorithms (see below) were employed to segment the image by the Season 1 crops (wheat, berseem clover, mustard, or vegetables), Season 2 crops (vegetables or other), and the Season 3 crops (rice or other).

For each cropping year and season, scenes from Landsat were identified. The imagery used is summarized in Table 1. A cloud-free Rapid Eye image was acquired for the site in February 2012. The image provided estimated reflectance at a five-meter spatial resolution in five spectral bands (blue, green, red, red-edge, and near infrared). The image was ortho-rectified and used to identify agricultural areas.

Table 1: Classification of data and remote sensing imagery used to identify presence or absence of individual crops at times when they are likely to be visible by remote sensing

<i>Date (Year-DOY)</i>	<i>Sensor</i>	<i>Classes</i>
Season 1 (November 15 - April 15)		
2011-01	RapidEye	urban, forest, fallow, berseem, mustard, wheat, vegetables
Season 2 (April 15 - June 15)		
2011-143	Landsat 7	fallow, vegetables
2011-151	Landsat 5	fallow, vegetables
Season 3 (June 15 - October 15)		
2011-263	Landsat 5	fallow, rice
2011-271	Landsat 7	fallow, rice

For the winter season, a random forest classifier (Scikit-learn 2013) was used with the training polygons provided by ground truth, along with some added training sets to identify urban, forest, river, and other non-agricultural areas. A random forest classifier utilizes several decision-tree classifiers on multiple subsets of the data and averages the results. The implementation used was from the open-source python library ‘scikits.’

For the spring season, a NDVI (Normalized Difference Vegetation Index) (Rouse et al. 1973) threshold was used to identify green pixels in the agricultural areas, which were taken to be growing vegetables. A threshold was determined visually to obtain the best coverage of the non-fallow areas as determined by the visual interpretation.

For the summer season, an LSWI (Land Surface Water Index) (Chandrasekar et al. 2010) threshold was used in conjunction with the NDVI to identify areas that could be visually determined to be like water. The river regions (and other non-agricultural regions) were then masked out to generate a map of likely rice paddies.

There was some ambiguity due to the small field sizes (typically 15 x 15 m and sometimes as small as 5 x 5 m) and highly heterogeneous nature of the landscape. At this scale, nearly all of the 30 m Landsat pixels contain mixed information from multiple farm fields. Even the 5 m RapidEye data frequently contained mixed information, making estimate of error difficult.

Agricultural area accounted for 82.2 % of total land; the rest consists of urban, suburban, and forested regions. The makeup of crop rotations within the agricultural land is shown in Table 2. Using the multiple crop rotation maps, the average land cover for each class was determined, along with a standard deviation, as shown in Table 2.

Table 2: Crop rotation land cover

Season			% of Agricultural Land	
Season 1	Season 2	Season 3	Mean	Std Dev
Wheat	-	Rice	74.1 %	1.3 %
Berseem clover	-	Rice	11.0 %	0.3 %
Mustard	-	Rice	4.8%	0.1 %
Winter Veg	Summer Veg	Rice	3.8 %	0.1 %
Winter Veg	Summer Veg	-	0.5 %	0.1 %
Wheat	-	-	4.0 %	1.3 %
Berseem clover	-	-	1.1 %	0.3 %
Mustard	-	-	0.6 %	0.1 %

2.1.4. Uncertainty qualification

Every classification approach has some amount of uncertainty. However, due to the lack of training data for the spring and summer seasons, uncertainty estimates could not be made based on ground-truthed data. Since there were multiple scenes for each of the spring and summer seasons, multiple classifications resulted. These multiple rotation maps were used as an indication of the uncertainty due to temporal differences, such as un-modeled atmospheric variables. The low error levels demonstrate there is a high agreement across multiple observations.

The authors estimate that a likely source of error is unknown temporal differences that cannot be measured from a single observation. Multiple observations were used for both the spring and summer seasons. When all the scenes (one for winter, two for spring, two for summer) were combined to generate crop rotation classes, four possible combinations result. Pixels with a clear and certain crop will have that class in most of the maps. Areas with mixed and uncertain classes will be classified differently in each classified map.

Each classification map was assigned the appropriate emissions in $\text{kgCO}_2\text{e/ha}$, and the resulting ensemble was considered to follow a normal distribution. The mean and standard deviation of the sum of each map resulted in the total emissions for the region, with error bounds. This was divided by the total area of agricultural land to determine the emissions per hectare.

To calculate the total amount of error, the combined weighted variance was calculated from all modeled sources of error. For the Karnal case study, this included the variance due to unknown soil types as well as the variance in total population of each crop rotation. If there were additional modeled sources of error, these could easily be included in the weighted sum of the variances.

2.2. Results

DNDC model results by crop rotation are provided on a per hectare and regional basis below.

Table 3: Global warming potential rates

Scenario	% of Ag. area	Yield (kgDM/ha/y)	GWP (kgCO ₂ e/ha/y)				
			dSOC	CH ₄	N ₂ O	total GWP	Soil σ
rice-wheat	74.2%	8,336	630	7,878	1,937	10,445	1,806
rice-berseem clover	11.0%	14,594	899	6,805	3,098	10,802	1,729
rice-mustard	4.8%	5,707	796	7,466	2,537	10,799	1,847
wheat	4.1%	4,190	230	-13	366	584	133
rice-vegetables	3.8%	14,831	692	3,173	3,919	7,784	888
Berseem clover	1.1%	15,179	370	-11	1,793	2,152	381
mustard	0.6%	1,456	375	-11	446	810	176
winter veg.- summer veg.	0.5%	10,785	356	-10	2,671	3,018	412

Table 4: Global warming potential totals

Scenario	Ag. Area	Ag. σ	GWP (tonnes CO ₂ eq)			
	(ha)		Total GWP	Soil σ	Class σ	Total σ
rice-wheat	5,940	127	62,042	10,728	1,322	10,809
rice-berseem clover	881	29	9,521	1,524	316	1,557
rice-mustard	388	14	4,188	716	147	731
wheat	325	126	189	43	73	85
rice-vegetables	301	14	2,345	268	106	288
Berseem clover	86	29	185	33	63	71
mustard	47	14	38	8	11	14
win. veg.-sum. veg.	37	14	111	15	41	44
Total	8,005		78,620	13,335	2,079	13,598

Methane emissions were the dominant source of GHG emissions for the crop rotations with rice. Differences in modeled emission for crops grown on the same soils and climate conditions were driven by crop residue conditions and management. The rice-wheat, rice-mustard and rice-berseem clover rotations had significantly higher methane emissions than the rice-vegetable rotations. Our field surveys indicated that crop residues were burned, thus we assumed that 95% of aboveground crop residues were removed at harvest. Despite low litter additions to soil C, high modeled methane (CH₄) emissions for the rice-wheat, rice-mustard and rice-berseem rotations were due to anaerobic decomposition during the rice cropping season of high residue root biomass following harvests of wheat, berseem clover, and mustard crop.

Results indicate a loss of SOC from all cropping systems. The losses ranged from 230 to 899 kgCO₂e/ha with higher SOC losses in the rice rotation systems. This was due to anaerobic decomposition and increased soil disturbance due to more intense tillage under the multiple crop rotations. Loss of SOC accounted for 8% of the total GHG emissions. Nitrous oxide emissions varied from less than 1 kg N-N₂O/ha/yr to around 8 kg N-N₂O/ha/yr. Variability was largely due to differences in nitrogen fertilizer application rates. Total N₂O emissions accounted for 24% of the GHG emissions.

The agricultural area in Karnal (~8,005 hectares) showed mean GHG emissions of 9.8 tCO₂e/ha/yr. Accounting for uncertainty in the crop rotation maps and soil condition at a 95% confidence interval leads to a range of 6.4-13.2 tCO₂e/ha. Therefore, over the entire site the net emissions from agriculture were estimated to be 78,620 tCO₂e/yr with a 95% confidence interval of 51,212-106,028 tCO₂e. The rice-wheat, rice-berseem clover, and rice-mustard rotations were the dominant sources of GHG emissions in Karnal. The rice-wheat system accounted for almost 75% of the cropland area and accounted for 79% of the total greenhouse gas emissions. The rice-berseem clover and rice-mustard rotations accounted for approximately 12% and 5% of total emissions, respectively.

Soil conditions were the major source of modeled uncertainty and were largely driven by DNDC sensitivity to soil texture and SOC on net methane and nitrous oxide emissions.

3. Sensitivity analysis

Uncertainty in model simulations is at least partially determined by sensitivity to model inputs. To capture variability in emissions accurately, a certain level of precision is required for each input. To streamline the collection and prioritization of model inputs (field work and background research) it is critical to know which parameters are most influential (and, conversely, which variables have little to no effect). As a way to illustrate issues of model sensitivity to inputs, using the Karnal site as a basis for geography and crop management, we varied several input parameters, including soil attributes, crop timing, organic inputs, and fertilizer N rates, and analyzed the model results.

The Karnal site has one major rotation (rice-wheat; 85% of agricultural area) and three other common rotations (rice-berseem clover, rice-mustard, and rice-vegetables; 4%, 4%, and 8% of agricultural area respectively; Gopal Bhatta, unpublished data). Other single-crop rotations are uncommon (berseem clover, mustard, wheat, and vegetables). The Karnal site is dominated by rice, but to demonstrate DNDC's sensitivity to inputs for upland crop systems, we also looked at crop rotations where rice was replaced with maize. There are significant differences between the combined annual GWP for crop rotations at Karnal; notably however, there are some rotations that are not statistically different (e.g., rice-wheat, rice-berseem clover, and rice-mustard are not distinguishable via t-test, $p < 0.01$, see Fig. 1), suggesting that remote sensing analyses could be simplified to focus on distinguishing only rotations with different GWP profiles. Given the similarities in the emissions profiles for the common rotations, we look only at the dominant system (rice-wheat) and its upland proxy (maize-wheat) for subsequent analyses.

We looked at the effects of varying each of the four key soil inputs to DNDC (clay fraction, SOC, bulk density, and pH) on GWP. To test each soil attribute, we looked at the low (90% of mean) and high (110% of mean) values for each attribute while keeping all other attributes constant.

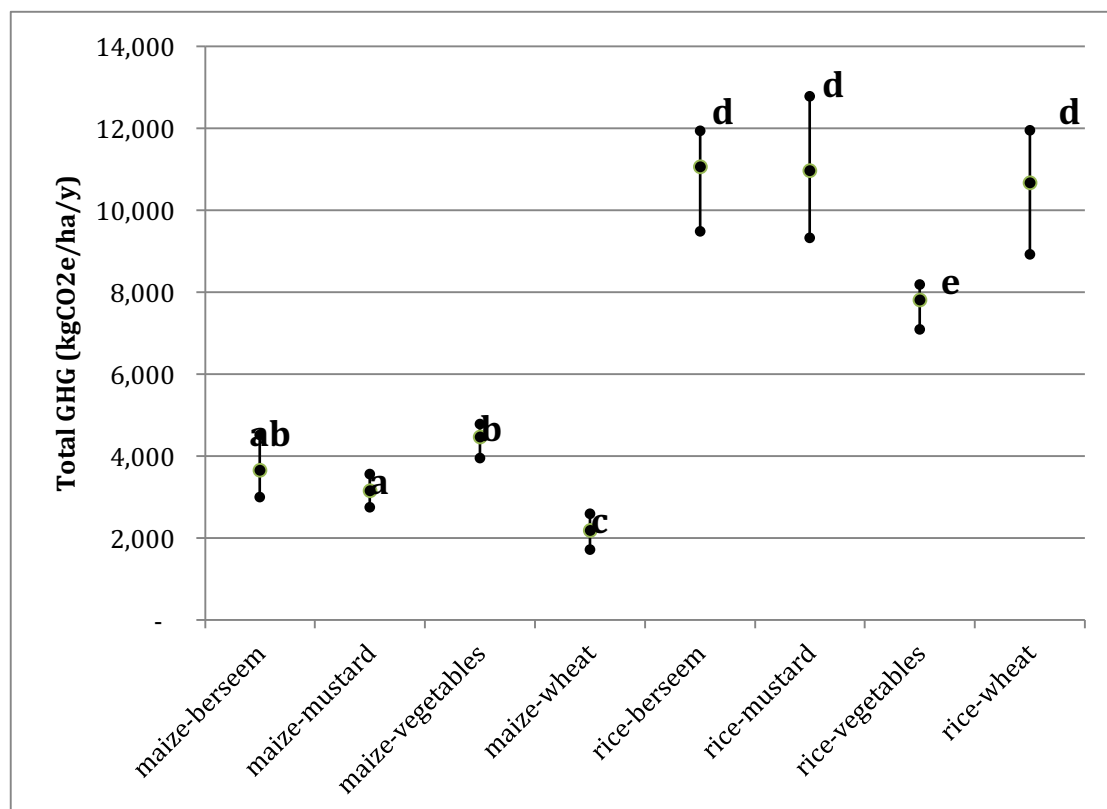
High clay soils showed suppressed GWP from reduced CH₄ emissions: gas transport through heavier soils is reduced, which increases CH₄ residence time in the soil and thus attenuates emissions through larger relative methanotrophy and adsorption of dissolved organic carbon (DOC). This is a similar finding to elsewhere in Asian rice systems: Li et al. (2004) found that

CO₂, CH₄, and N₂O emissions (and hence net GWP) were inversely proportionate to clay fraction in rice-winter wheat rotations in China and Babu et al. (2006) found that CH₄ was moderately inversely proportional to the clay fraction in Indian rice crop rotations.

As SOC increased, CO₂, CH₄, and N₂O emissions increased due to expanded microbial biomass. This, in turn, enhanced decomposition (CO₂ emissions) and methanogenesis (CH₄ emissions) and increased soil N mineralization (N₂O emissions) over the timeframe of the simulation. CO₂ and N₂O vary substantially and CH₄ varies moderately proportionally with soil SOC in rice-wheat rotations in China (Li et al. 2004). CH₄ varies moderately with increasing pH in Indian rice crop rotations (Babu et al. 2006).

Bulk density and pH had only marginal effects on rice-wheat GWP. However, bulk density had a notable effect on maize-wheat GWP.

Fig. 1 Crop rotations at the Karnal site. Letters a-e indicate statistically significant similarity. This figure also illustrates variability in GWP across soil types at the Karnal site.



The fact that soil attributes vary substantially over space, and even over small areas like a single farm field, suggests that (a) soil attribute variability in each HWSD polygon may not well represent the variability at this site because it is such a small fraction of the polygon and (b) uncertainty in site GWP from soil attributes stems not only from uncertainty in the location of soil attributes within the soil polygon, but in the uncertainty of the soil polygon itself (which is necessarily highly generalized).

Synthetic N fertilizer rate and timing can have significant effects on N₂O emissions. N₂O emissions generally increase with increasing N application in rice systems (Pathak et al. 2005, Li et al. 2004, Babu et al. 2006), except for soils with low N and high levels of crop up-take. N fertilizer applied in place of organic N inputs (green manure or wheat straw) can increase N₂O emissions (Babu et al. 2006). When the N fertilizer rate was adjusted from 90% to 110% of actual, combined GWP followed expected patterns at Karnal; i.e., GWP increased principally due to increases in N₂O emissions.

Organic fertilizers can affect both N₂O (to the extent that they create surplus NH₄ in the soil environment) and dSOC and CH₄ in rice systems (to the extent that they add carbon to the soil, in whatever form). Rice straw incorporation has substantial effects on CH₄ emissions (Li et al. 2004), and timing is important as emissions are significantly different when applied just prior to planting, or in-season versus post-season (Sander et al. 2014). Various types of green manure—rice straw and compost—applied in combination with N fertilizer can increase CH₄ emissions over N fertilizer applied alone (Babu et al. 2005). At the Karnal site, increases to organic amendments had little effect on upland emissions (a small decrease to dSOC was offset by a small increase in N₂O) but had the expected larger effects rice CH₄.

We simulated two different floodwater management options: continuous flooding (CF) and rain-fed (using the rain-fed option in DNDC simulates the paddy water table based on available water from precipitation moderated by DNDC's evapo-transpiration sub-model). Simulating rain-fed systems generated lower GWP due to reductions in CH₄ emission. The Karnal site has relatively low mean annual precipitation (326 mm/yr) over the simulation timeframe and is inconsistent enough through the rice season to allow paddies to partially dry and reduce anoxic conditions.

Increased crop residue and residue incorporation can increase net emissions, principally by increasing CH₄ emissions (in rice systems via increased soil C source) and N₂O emissions

(increased soil N mineralization from increased SOM), despite decreased CO₂ emissions from sequestration (Li et al. 2004). At the Karnal site, increasing the residue fraction from 4.5 to 5.5% had negligible effects on the upland rotation but showed the expected effect of a small CH₄ increase from increased soil C substrate availability to methanogenic microbes.

Increasing the duration of the season had minor effects on the upland rotation (minor increases to CO₂ emissions were offset by decreases to N₂O emissions from increased plant N uptake). Similar CO₂ and N₂O effects were seen on the rice rotation, however, CH₄ emissions increased due to the longer duration of the rice crop (the principal CH₄ soil-atmosphere pathway).

DNDC requires local weather data (temperature and precipitation at minimum) to drive crop growth and soil processes. We did not evaluate weather drivers here, but increased temperature should increase soil microbial activity and thus increase CO₂, CH₄, and N₂O emissions. Precipitation should affect N₂O emissions in upland crop systems (aerobic soils) as N₂O emission is mediated in part by soil moisture (Li et al. 2004). Precipitation has little effect on emissions from rice, except in rain-fed systems where dry periods could affect soil moisture status (thus reducing CH₄ emissions and, in the presence of ample soil nitrogen, increasing N₂O emissions).

Figure 2 is an illustration of the relative effects of each input. We calculated the relative effect (%) as:

$$\text{Relative effect} = \text{change}_{\text{input}} * \text{change}_{\text{gwp}}^{-1}$$

Where,

$\text{change}_{\text{input}}$ = the difference between the high and low inputs as a percent of the mean input

$\text{change}_{\text{gwp}}^{-1}$ = the absolute difference between the high and low GWP result as a percent of the mean GWP result

Figure 2 Relative effects of key inputs* to the DNDC model for (a) rice-wheat and (b) maize-wheat

Figure 2a

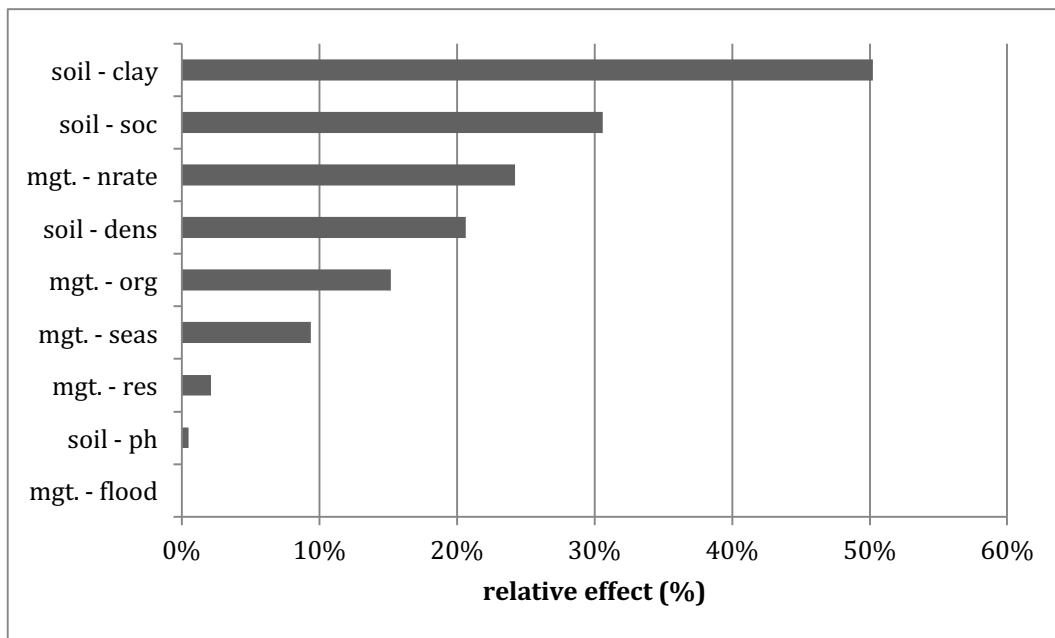
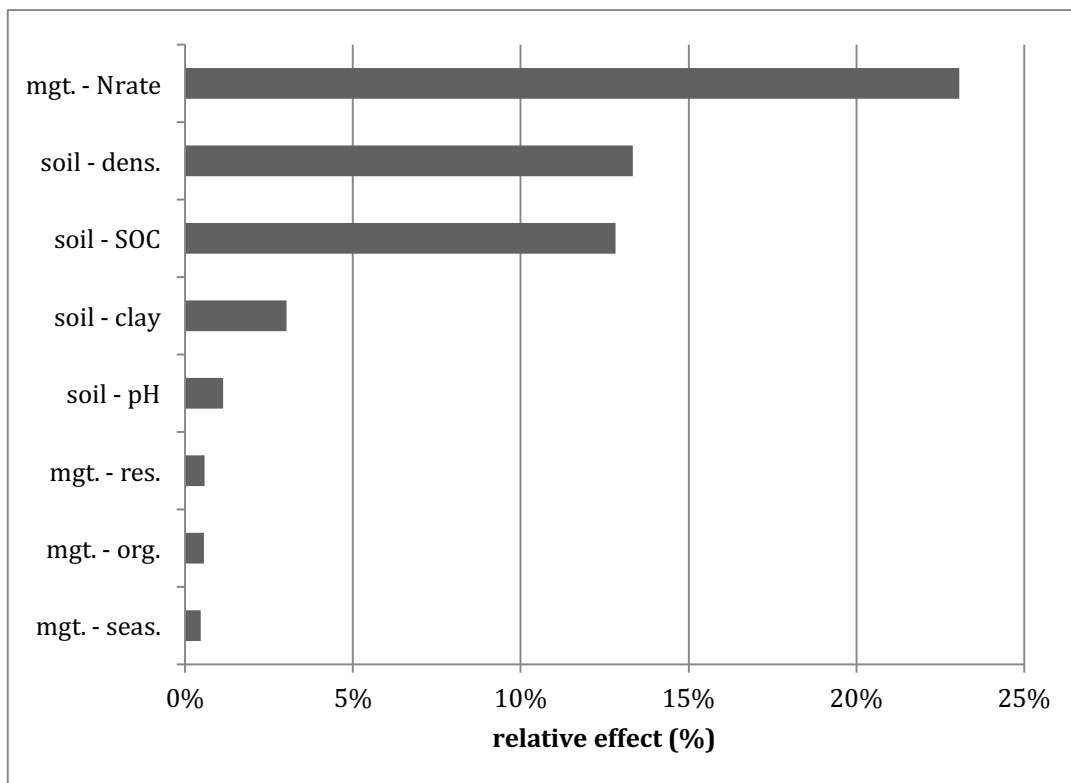


Figure 2b



* Key inputs described in table: mgt = management; org. = organic matter application; res. = crop residue; seas. = season

4. Recommendations

In this section, we outline a method to combine remote sensing, fieldwork, and GHG simulations for GHG quantification with low cost and low uncertainty. Our view is that field campaign costs can be reduced by optimizing data collection, which requires focusing on the most important model inputs. In addition, we believe that remote sensing efforts can be made more efficient through *a priori* simulations of crop rotations and proper coordination with field work. Because of the complex interplay between field and ancillary data, remote sensing analyses, and GHG simulations, it is difficult to prescribe a rigid process or even an exact order. For instance, remote sensing can be made more efficient by having final emissions data available (rotations with the same emissions need not be discriminated); conversely, the work to prepare and simulate GHGs could be made more efficient if the area of a rotation is found to be negligible based on remote sensing was not simulated. In all likelihood an iterative process proceeding toward increasingly refined analyses would have to be adopted. We suggest the following process would apply in most cases:

1. Background research & planning
2. Field data collection
3. GHG simulation
4. Remote sensing analyses
5. Uncertainty analysis

4.1. Background research

We recommend gathering available data about the site as a first step, prior to selecting imagery. This might include available agricultural statistics, including yield, crop area, etc., GIS data and prior remote sensing-based products, and remote expert interviews. A preliminary understanding of typical crops and their seasonality, field areas, and crop management would facilitate improved selection of appropriate remote sensing imagery in terms of type (e.g., optical versus synthetic aperture radar (SAR)), resolution and scale (fine versus coarse), and timing (temporal consistency between key cropping timeframes and image dates). In addition, this would facilitate preliminary selection of ground truth points and the identification of key ground targets for field investigation. This is particularly important in

areas with smallholder agriculture where remote identification of large targets is crucial for calibration.

4.2. Field data

In addition to fulfilling research design sampling requirements (appropriate sample size and strategy), a field data collection campaign should be designed with remote sensing requirements in mind and targeted to collect data for key model inputs. The field campaign should identify all major crop rotations and their seasonality so that appropriately timed remote sensing images can be acquired. Weather is a key driver of biogeochemical processes. Whenever possible, local weather data should be acquired, and this process may be simplified by the presence of a team familiar with local sources. Information about N fertilizer application rates is essential as the principal driver of N₂O emissions and crop growth (see Fig. 2). Fertilizer form is less important, for example Li (2004) found all GHG emissions to be relatively insensitive to fertilizer form. In wetland systems (i.e., rice), care should be paid to carbon inputs (organic amendments and residue amounts) as changes to SOC can have significant effects on CH₄ emissions. Other aspects of management such as seasonal and flood duration, tillage timing, should be collected to approximate the growing season dynamics appropriately. However, precision is less of an issue as these inputs have only minor effects on outcomes.

Soils characteristics are key drivers of biogeochemical processes. At the Karnal site, for both rice-wheat and maize-wheat rotations, soil attributes represent three of the top four most sensitive variables determining GHG emissions (see Fig. 2). Soil data present a daunting challenge when working in the developing world: comprehensive and high-resolution survey data are rarely available, and data that are available, while potentially accurate, are imprecise both in terms of spatial resolution (e.g., HWSO) and confidence intervals around soil attributes (e.g., ISRIC SoilGrids1km; ISRIC 2013). In addition, soil testing is expensive and time-consuming, even if facilities even exist near the field site to perform soil analyses. That said, soil properties (particularly clay and SOC fraction) are important drivers of GHG emissions and data that are imprecise are a significant source of uncertainty. For instance, at the Karnal site, soil uncertainty represented 98% of total uncertainty. As with any modeling effort, uncertainty is inversely proportional to input data precision and cost. Cost-benefit tradeoffs with soils data include using coarse data (least precise, but inexpensive), improved

precision with soil surveys (most precise, but expensive), soil modeling via remote sensing or other GIS data (precise, but time consuming and with potentially limited accuracy; see Croft et al. 2012, Vagen and Winowiecki 2013), and producer questionnaires. Producer questionnaires may be useful in some areas where soils data are poor and farmers know the soil properties of their fields. If enough farmers can be surveyed to be able to extrapolate soil properties across a landscape, this could be effective and done with minimal added costs.

4.3. GHG simulations

Where feasible, some analysis of GHG emissions be carried out prior to remote sensing analyses, preferably using the selected model software (due to the increased precision and site applicability). This would facilitate a more efficient mapping process so that a classification scheme could be developed that discriminates only between agricultural land cover classes which differ by GHG emission (e.g., see Figure 1), potentially reducing analysis time and cost and increasing map accuracy, while reducing map uncertainty.

The DNDC model has the advantage of being one of the only major biogeochemical models used in agro-ecosystems that simulates both C (CO₂ and CH₄) and N dynamics, as well as phosphorus, to a more limited extent. Thus, to calculate all the major aspects of GWP generated at a site (dSOC/CO₂, CH₄, and N₂O), only a single set of inputs and outputs is required. In addition, DNDC offers great flexibility over a large set of farm management practices and crops and delivers highly precise and comprehensive results. Its disadvantage is the that DNDC requires a large amount of input data and, as with any model, the quality of its output is highly related to the quality of the inputs. Thus, in data-poor areas, these facts can lead to a situation where either (a) many input assumptions are required, leading to uncertain results, or (b) intensive data-gathering is required, leading to high costs.

Other major models generally are not as comprehensive in terms of crop modules and output (e.g. APSIM, Keating et al 2003) or have more intensive processing time or input requirements (e.g., ECOSYS) (Grant 2014, Smith et al. 2008). The DayCent model (Parton *et al*, 1998) is similar to DNDC in many respects and has been validated in many different regions. Its advantage over DNDC is in having more precise control over soil profile characteristics; however, this potentially requires additional inputs and processing time on top of its already intensive long-term SOC initialization phase using native vegetation (Smith et

al. 2008). DNDC accepts SOC as an input and can be equilibrated via 5 to 10 years of initialization (Perlman et al. 2013).

4.4. Remote sensing

The type of remote sensing data to be utilized will largely depend on the crop details, as determined by the background research and the quality and quantity of field data received. Optical imagery is particularly useful for identifying patterns of greenness associated with vegetation while SAR imagery provides useful data about surface water and vegetative biomass.

During the background research phase, the area of interest should be examined with any available remotely sensed imagery. Recommended sensors, along with details of their utility, are described below. This will enable the analyst to identify the quality and availability of data for the area and perform an initial assessment of spectral separability in the region. This may be limited to general classes (e.g., water, urban, forest, agriculture). However, some individual crops may be separable. By analyzing multiple large fields, the analyst can determine how many different classes can be feasibly separated. This may be done with multiple iterations of a k-means (MacQueen 1967) or similar unsupervised classifier, or even just examining average spectra for different fields across the region. Summer data may be used to classify among major crops, while spring scenes may be used to determine the presence of growing vegetables (using NDVI), and winter scenes may be used to detect flooded regions (using LSWI and NDVI) that are typical of rice paddies.

The data will usually need to be pre-processed, a step that can be largely performed before or during the field data collection. This involves ortho-rectification, radiometric correction (conversion of digital number to top-of-atmosphere radiance), atmospheric correction, calculation of appropriate index bands such as NDVI, and image mosaicking where appropriate. In areas with a prolonged rainy season, there is a high likelihood of cloud cover for any given sensor scene. Precise masking of the clouds is important to maximize the available data for mapping, but may still greatly reduce the amount of usable data due to the climate in the regions of interest.

After the field data are collected, the available sensor scenes can be used to perform supervised classification using the field data as training data. While we have used rpart

decision tree classifier (as described in Therneau and Atkinson 2013), and the random forest classifier (Scikits-learn 2013) from Scikits for past work, other supervised classifiers can be used. In fact, ideally an analyst will utilize several supervised classifiers and examine the differences and agreement among them.

4.4.1. Sensors

Following is a summary of each of the recommended sensors. We discuss several free (Landsat, MODIS) and low-cost (PALSAR) sources of imagery in addition to higher-cost commercial imagery. Each sensor provides information at a spatial resolution (i.e., the size of a pixel) and temporal resolution (i.e., frequency of repeat images) for a given field of view. A higher resolution per pixel means a smaller field of view since it is limited by the size of the imaging array. Furthermore a smaller field of view means it takes longer to image the earth. A sensor can be high resolution, or it can have a high revisit time, but it cannot have both. The most complete picture of agriculture in a region will be obtained by combining information from multiple satellite sensors and calibrating these observations with ground surveys.

The Landsat sensors (now Landsat 7 and 8) provide a moderate resolution of 30 meters and a revisit time of 16 days. Landsat 7 and 8 have alternating orbits: thus one of the Landsat sensors will revisit every location every eight days. Landsat 7 has a current issue where the scan line corrector, a set of mirrors used to correct for the along-track motion of the satellite, failed. This results in strips of no data regions that get larger the further away from nadir. Landsat 8, launched in 2013, has greater accuracy as well as some additional spectral bands that are useful for better masking of clouds. Due to the number of spectral bands, Landsat can be effectively used to create a land use map as long as the fields are of sufficient size. At the basic level this would at least include the ability to map water, urban, forest, and agricultural regions. Some crops may also be separable, a factor that depends on the difference in the crops' spectral signature. This highly depends on the individual crops and would be determined by analyzing ground truth data and temporally matched Landsat scenes. This calibration step will produce the complete set of classes that can be expected to be reasonably separated.

The MODIS sensors Aqua and Terra are much lower resolution (250m for red and NIR bands, 500m for visible, SWIR and LWIR, and 1000m for the remaining bands), but have a larger number of bands and a shorter revisit time. The additional bands allow for wider variety of

products to be derived, although many of them are for ocean and atmospheric applications and thus not applicable to remote sensing for agriculture. The lower resolution of the MODIS sensors makes them unsuitable for mapping and identifying individual fields. However the higher revisit time (one to two times/day depending on latitude) are useful for determining an approximate crop calendar, at least across large regions. Although planting and harvesting dates for individual fields may vary, it is dependent on local weather patterns and thus roughly consistent across local regions. MODIS can be used to estimate these dates by looking at large-scale trends across the study site.

Radar backscatter from active sensors, such as PALSAR from the Japanese space agency JAXA, provide information about surface water and vegetation biomass. Radar sensors also have the advantage of being able to penetrate through clouds. These features make them well suited for detection of rice fields, even in the presence of extensive cloud cover.

In addition to the sensors noted above, there are several sources of commercial imagery including Quickbird, RapidEye, and IKONOS. Their advantage is their high spatial resolution (1-5m), which makes them useful for visually identifying landscape features, agricultural fields--especially in developing-world smallholder contexts-- and generating masks of water and urban regions. Each commercial satellite has different imaging characteristics, though most only have a limited number of bands (typically 3 visible and a near-infrared band) and irregular revisit times since they are often tasked to collect customer specified regions. The lack of multiple collects over time makes commercial imagery generally unsuitable for land use mapping. Because of the high costs of commercial imagery, there is generally not a benefit in terms of classification accuracy; the higher costs do not outweigh the potential classification advantages.

4.5. Uncertainty

Model uncertainty can be viewed in two ways: as a function of the inputs, as handled in the Karnal case study, and as a function of the inherent structural uncertainty of the model. Input uncertainty can be controlled for to some extent in accounting efforts through quality control of data research and collection. Depending on how survey data and input assumptions are handled, input uncertainty can be quantified via Monte Carlo simulations, and sensitive inputs such as SOC and fertilizer N rate can be varied to develop confidence intervals around mean

results. Structural uncertainty can only be reduced by improving the model itself. Quantifying and reporting structural uncertainty requires field-measured data paired with simulated results of the same field experiments for the landscape in question. This is a potentially time-consuming and expensive exercise and potentially not realistic for non-model developers. However, global model uncertainty for each reported constituent (CH₄, N₂O, etc.) could potentially be reported for the model as a whole with the assumption that the region in question fell in the range of total model uncertainty. Datasets are becoming available via the Global Research Alliance Modeling Platform (GRAMP) website for DNDC as well as other agro-ecological models that would facilitate comparisons of measured versus modeled results for multiple crop-systems in multiple geographies (Babu et al. 2014).

5. Conclusion

Low-cost landscape GHG accounting in developing world smallholder contexts is a necessary, but challenging endeavor. The approach in our case study site in Karnal, India is a step forward in terms of integrating remote sensing, field work, and biogeochemical modeling. However, it is limited by challenges of spatial scale and heterogeneity and available ancillary data (particularly for soils). These limitations lead to greater uncertainty in both remotely sensed maps and model simulation results. Our sensitivity analysis for both upland and wetland crops (rice), in combination with similar efforts by other researchers, demonstrate that there are a few very important variables that must be captured to reduce uncertainty, particularly fertilizer N rate, SOC, clay fraction, and bulk density. Our recommendations include a two-phase approach where efficiencies can be gained through an investigation of temporal and spatial farm scales in the geographic landscape and cropping patterns. . Through careful consideration of model sensitivity to external parameters such as crop management, weather, and soils, and spatial heterogeneity, a field campaign design can be streamlined to minimize effort and therefore cost. There are several sources of free high-quality, moderate spatial resolution data that, with proper planning and coordination with biogeochemical modeling and field work, can be used effectively for crop mapping. Uncertainty should be estimated for all aspects of the accounting effort through an integrated process. Remote sensing inaccuracies stemming from issues of contrasting temporal and

spatial scale between landscape and imagery should be combined with model variability from input parameters and overall model structural uncertainty.

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