Exploring the potential contribution of irrigation to global agricultural primary productivity

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[1] The potential contribution of irrigation to global agricultural net primary productivity (NPP) was explored using the Carnegie Stanford Ames Approach (CASA) model, modified for irrigation inputs. Excluding the effects from cultivar choice, fertilizer application, and water availability, removing climatic constraints to productivity through irrigation has the potential to increase carbon uptake by global cropland areas (which already have an average carbon uptake rate in excess of 175 $gC/m^2/yr$) by an average of 25 $gC/m^2/yr$ with a maximum of 627 $gC/m^2/yr$, especially in heavily irrigated semiarid areas such as northern India, the Indus River Valley, northeast China, the western United States, and the Nile River Valley. When accumulated across all irrigated areas and years, the total contribution of irrigation could exceed 0.40 Pg C per year, a value equivalent to the total NPP of U.S. croplands (0.41 PgC). The results also reveal that the relationship between cropland productivity affected by irrigation and climatic moisture availability is nonlinear: in locations that receive less than 1500 mm/yr rainfall, cropland productivity has a strong response to moisture; as humidity increases, additional moisture has very little impact on the productivity of crop areas. Moreover, the relationship between irrigation amount and productivity increase is also nonlinear: in humid locations, NPP response to irrigation is small but persistent; as aridity increases, irrigation has a substantial impact but its effect quickly saturates for irrigation input above 800 mm/yr, which may point to the efficiency of irrigation for different precipitation regions.

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1. Introduction

[2] Agricultural systems play a major role in the global carbon balance, contributing close to a fifth of carbon fixation as products of photosynthesis [*Potter et al.*, 1993; *Malmström et al.*, 1997; *Schimel et al.*, 2001; *Haberl et al.*, 2007]. While crops are often seasonally consumed and respire back to the atmosphere both locally and globally, carbon fixed via terrestrial net primary productivity (NPP) in agricultural settings has a strong influence on seasonal and horizontal oscillations of atmospheric CO_2 [*Keeling et al.*, 1996; *Ciais et al.*, 2007]. Moreover, carbon extracted from the atmosphere by crops may also be transferred to the soil through root production and residues following harvest, thereby driving soil organic matter dynamics and net carbon balance [*Eamus*, 2001; *Haberl et al.*, 2007]. As more countries move toward complying with post-Kyoto greenhouse gas emission commitments, effective carbon management strategies in the agricultural sector will increasingly require new scientific information about carbon flux processes and the interactions of climate, carbon, water, and nutrient cycles. Such management strategies will also require an ability to account for all carbon stocks and fluxes, including those influenced by agricultural management practices such as irrigation [*Bradford et al.*, 2005a].

[3] A long line of studies suggests that water is a major limiting factor in terrestrial carbon uptake across a range of spatial scales [*Rosenzweig*, 1968; *Leith*, 1976; *Stephenson*, 1990; *Churkina et al.*, 1999]. At the leaf level, water influences the partitioning of carbon and nitrogen between photosynthetic and nonphotosynthetic tissues and controls photosynthesis and stomatal conductance rates [*Ball et al.*, 1987; *Ghannoum*, 2009]. Across large areas, ecosystem water stress, caused by both soil and atmospheric deficits, affects light interception efficiency, ecosystem respiration, and leaf area index, greatly influencing the spatial and temporal variations in NPP.

[4] In the context of agriculture it is widely known that irrigation results in higher crop yields by sustaining adequate soil moisture throughout the growing period [*Bradford et al.*, 2005a; *FAO*, 2002; *Lobell et al.*, 2009]. What is less clear is the contribution of this yield increase, which is tightly coupled to carbon and nutrient uptake, to NPP and the carbon cycle at global scales. While irrigation has been incorporated

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into model-based NPP calculations [e.g., *Bondeau et al.*, 2007; *Haberl et al.*, 2007], these studies evaluated irrigated agriculture in the context of human appropriation of products of photosynthesis but did not document irrigation impacts on the terrestrial carbon cycle.

[5] The goal of this research was to explore the potential contribution of irrigation to global agricultural NPP in the year 2000 using the Carnegie Ames Stanford Approach (CASA) ecosystem model [*Potter et al.*, 1993]. The CASA model is designed to estimate monthly spatial patterns of carbon uptake, nutrient allocation, soil carbon, and CO_2 exchange using remotely sensed inputs and climate drivers. The spatial distribution of NPP, in particular cropland NPP calculated by CASA, could be used as a basis for exploring the range of modifications to terrestrial carbon sources and sinks through agricultural management practices. Moreover, maps of irrigated cropland NPP in conjunction with the spatial distribution of irrigation water use could enhance our understanding of the efficacy of irrigation in enabling or raising global NPP (or crop yield equivalent) and the potential for carbon sequestration through agriculture.

2. Methodology

[6] NPP (or its yield equivalent) is an important characteristic of agricultural systems and much effort has been expended to determine both short- and long-term variations in NPP at various spatial scales [*Hicke et al.*, 2004; *Bradford et al.*, 2005a; *Huang et al.*, 2007; *Bondeau et al.*, 2007; *Zaks et al.*, 2007]. In studies involving the productivity of agricultural ecosystems, NPP is advantageous over traditional agronomic units of yield because it allows a direct linkage to carbon cycle research and provides useful information for understanding feedbacks to the environment. In the research presented here, the CASA ecosystem model was used to explore the changes in global cropland NPP under irrigated conditions and evaluated the relationship between NPP and other environmental flows. Note that, to model cropland NPP influenced by irrigation, only the existing moisture down-regulators in the CASA model were modified. While there are many other human factors including the decision to fertilize crops, availability and use of modern varieties optimized for irrigated/fertilized conditions, and politics/economics of irrigation systems that strongly influence global agricultural NPP, none were considered in this study. Therefore, the research presented here should be viewed as a modeling exploration with the help of an ecological model to better understand the controls on global crop productivity from irrigation. In the following sections, the CASA model, the data sets used in the study, and the modifications are described.

2.1. The CASA Model

[7] The CASA model is designed to calculate NPP based on the light use efficiency (LUE) concept [*Monteith*, 1972], which quantifies the efficiency of plants to convert absorbed radiation into products of photosynthesis at characteristic and fairly efficient rates [*Potter et al.*, 1993; *Field et al.*, 1995; *Potter et al.*, 2007]. The LUE approach is particularly attractive for satellite-based estimates of NPP because light absorption of plants is the primary driver of net carbon uptake and can be directly measured over large areas using remote sensing [*Field et al.*, 1995]. CASA estimates monthly production of plant biomass as a product of absorbed photosynthetically active radiation (*PAR*) and a maximum LUE term ($\varepsilon_{\max}$) that is modified by stress scalars for temperature (T) and moisture (W):

$$NPP = PAR \times fPAR \times (\varepsilon_{\max} \times T \times W) \qquad (1)$$

The CASA model uses the satellite-derived Normalized Difference Vegetation Index (NDVI) to derive *fPAR*, or fraction of PAR absorbed by vegetation canopies, following the empirical formulation of *Los et al.* [2000]. In the original formulation, the $\varepsilon_{\max}$ term is set uniformly at 0.41 gC MJ^{-1} PAR for all biomes based on extensive calibration of predicted annual NPP to field estimates [*Potter et al.*, 1993]. The temperature down-regulator term (T) is calculated as the fractional deviation from an optimum temperature determined by latitude and seasonal timing of green biomass [*Field et al.*, 1995]. The water stress term (W) is computed as a function of water deficit based on demand (potential evapotranspiration) and supply (precipitation and stored soil water) and limits NPP by a maximum of 50 percent [*Field et al.*, 1995]. While CASA's soil moisture function is very similar to functions used in other models, the less restrictive function (i.e., the 50 percent maximum) in CASA reflects the evidence that water stress limits NDVI as well as $\varepsilon_{\max}$ [*Garcia et al.*, 1988]. The CASA model has been validated against field-based measurements of carbon fluxes across a variety of land cover types including croplands [*Potter et al.*, 1993; *Hicke et al.*, 2002; *Lobell et al.*, 2002].

[8] The soil submodel of CASA uses a set of differential equations, adapted from the CENTURY model [*Parton et al.*, 1992], for carbon and nutrient cycling. Respiration, carbon and nutrient fluxes are related to air temperature, soil moisture, litter quality, and soil texture through a series of non-dimensional indices. For example, litter decomposition is slower where litter quality is low (high lignin to nitrogen ratio) and microbial turnover rates decrease with soil particle size as the silt and clay content increases.

[9] In this study, the CASA model was modified by an adjustment of the moisture down-regulator (W) term to capture irrigation. However, due to observed higher LUE values in irrigated areas, the CASA $\varepsilon_{\max}$ term was first adjusted for irrigation before the moisture down-regulator modification, using the LUE values for 16 commonly planted crops under irrigated and nonirrigated conditions. To do this, the CASA model was first run iteratively with a range of maximum LUE values (0.1–1.2 g C MJ^{-1}) for each grid until a best match to reported NPP from *Monfreda et al.* [2008] data set was found. This procedure resulted in a spatially explicit LUE map. Then, using the fractional individual crop area from *Monfreda et al.* [2008] and the fractional irrigated area product of *Siebert et al.* [2007], average LUE values for the same 16 crops were extracted (Figure 1). In general, crop LUE in irrigated areas is up to 20% higher than for crops grown in nonirrigated areas. The two dashed lines in Figure 1 represent the mean LUE value across all crops considered here for each crop management system (0.41 versus 0.48 g C MJ^{-1}, respectively, for nonirrigated and irrigated areas). Finally, a new land cover type that included grids locations with at least 25 percent irrigation in the *Siebert et al.* [2007] data set was generated. The default $\varepsilon_{\max}$ value for this new

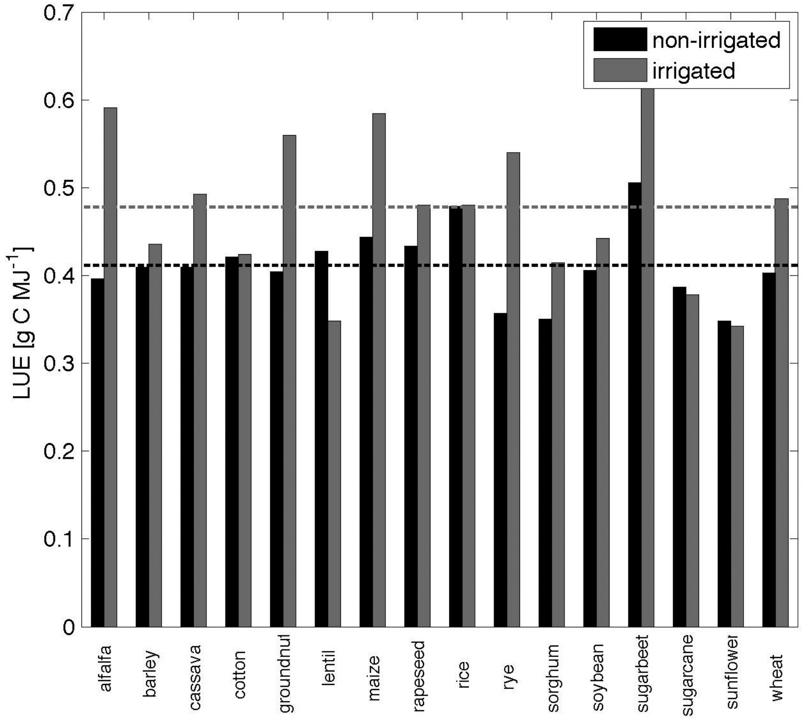

Figure 1. Spatially averaged Light Use Efficiency (LUE) value for 16 commonly planted crops under irrigated and nonirrigated conditions. Spatial distribution of LUE was estimated by iteratively running the CASA model with a range of maximum LUE values (0.1–1.2 g C MJ^{-1}) for each grid until a best match to reported NPP from *Monfreda et al.* [2008] was found. Crop-specific LUE was extracted using the crop-type data set of *Monfreda et al.* [2008]. In general, crop LUE in irrigated areas is up to 20% higher than for crops grown in nonirrigated areas. The two dashed lines represent the mean LUE value across all crops considered here for each crop management system.

irrigated cropland land cover class was set to the average of 16 crops (0.48 g C MJ^{-1}) while nonirrigated cropland maximum LUE value was set to the original 0.41 g C MJ^{-1}. Note that while the new ε_{max} estimate represents the average value across 16 common crops, the specific value of ε_{max} significantly varied among different crop types (Figure 1). For example, the ε_{max} for C4 crops (e.g., maize) is higher than for most C3 plants (e.g., wheat), owing to greater water use efficiency of the C4 assimilation pathways [*Lloyd and Farquhar*, 1994; *Lobell et al.*, 2002]. While this variation in ε_{max} was captured spatially in the procedure described above, it was not incorporated into CASA runs. Since the main purpose of this research was to isolate the irrigation effects, only a single ε_{max} value modified for irrigation presence was considered for all crops.

[10] To assess CASA's ability to predict cropland NPP with the default maximum LUE value, annual NPP measured as part of the BigFoot project [*Turner et al.*, 2005] was compared to the CASA estimates at the Bondville (Illinois, United States) agricultural station [*Meyers and Hollinger*, 2004]. Excluding nonvegetated areas like roads and builtup areas, the average reported NPP for this site was 573 ± 253 gC/m^2/yr based on flux tower data adjusted by remotely sensed estimates. For the same location, the CASA estimate of NPP for the year 2000 was 551 ± 55 g C/m^2/yr.

[11] To validate the outcome of the CASA model when irrigation was present, simulated NPP data were compared to observations at six irrigated agricultural sites for which NPP data exists (Figure 2). Different methods were employed at each site to determine irrigated agricultural NPP. At the Mead site (ME) the NPP data was obtained from *Verma et al.* [2005] where the measured crop yield data for 2000–2004 for both maize and soybeans were converted to NPP using the approach proposed by *Lobell et al.* [2002]. At the Yaqui Valey site (YQ), the aboveground biomass observations reported by *Lobell et al.* [2002] were converted to carbon equivalent assuming a 0.45 conversion ratio. Dr. Giorgio Alberti provided the NPP data for the Beano site in Northern Italy (BE) (Giorgio Alberti, personal communication, 2009) for both maize and alfalfa and averaged them over multiple years (2005–2008). The Harran site in southeastern Turkey (HA) is a large irrigated valley dominated by cotton for which lint yield for the period 1998–2002 were obtained from the *Turkish Statistical Institute* (2008) and converted yield to cropland NPP using the formulation of *Lobell et al.* [2002]. Finally, for both the Nile Delta (ND) and Northeastern India (NI) sites, NPP data were extracted from *Monfreda et al.* [2008], combining NPP of multiple crops grown ca. 2000. Note that in some sites (e.g., Beano), the date of CASA results and NPP observations do not match. However, due to irrigation availability to remove water stress and long-term cultivation history in each site, the interannual discrepancies are assumed to be minimal. This is verified (not shown) by some of the sites for which long-term yield data exist (e.g., the HA site).

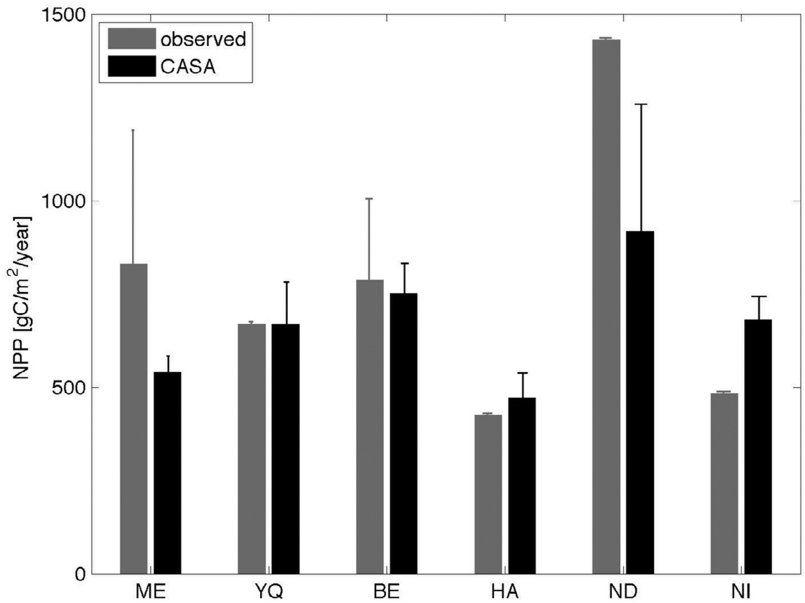

Figure 2. Comparison of CASA-predicted (gray) and observed (black) NPP for six irrigated sites. ME, Mead, Nebraska (United States); YQ, Yaqui Valley (Mexico); BE, Beano (Italy); HA, Harran Plain (Turkey); ND, Nile Delta (Egypt); and NI, northwestern India. The error bars reflect temporal variation around the mean. Please see section 2.1 for data and references.

[12] Note that it is very difficult to obtain observed NPP data in irrigated areas. In the United States, there is only one site (Mead, Nebraska) and in other countries there exists no flux locations in dryland irrigated areas. There are flux observations in irrigated paddy rice fields in China and Japan but these measurements were not available to this study. In the locations where no actual NPP (or its GPP equivalent) observations were available, other (and less exact) methods such as yield conversion were used to estimate NPP (Figure 2) and may contain some errors.

2.2. Adjustment of Light Use Efficiency for Irrigation

[13] The choice of method to account for irrigation in previous studies involving CASA [e.g., *Lobell et al.*, 2002] has been to set precipitation equal to potential evapotranspiration, in essence removing all climatic water deficit potential. To incorporate the effects of irrigation in this research, the approach proposed by *Potter et al.* [2007] was followed by modifying the maximum light use efficiency term, $\varepsilon_{\max}$, by reducing the impact of the moisture limitation as a linear function of irrigated area:

$$W_{irr} = W + [1 - W]f_{irr} \qquad (2)$$

In equation (2), W_{irr} is the new water stress factor adjusted for irrigation presence, W is the original water stress factor, and f_{irr} is the fraction of irrigated area in each location (grid) developed by *Siebert et al.* [2007]. Equation (2) simply reduces the effect of W as a linear function of fractional irrigated area, where the large extent of irrigation effectively removes the water stress as calculated by the soil moisture submodel described by *Potter et al.* [1993].

[14] The following example is useful to describe the effects of the water stress term modification. Consider a location with small vegetation presence (e.g., NDVI of 0.15) depicting an area without intensive crop production. When water stress is present, calculated NPP would be mere 34 gC/m^2/yr. When water stress is removed following equation (2) above, calculated NPP increases fivefold to 212 gC/m^2/yr. This potentially irrigated but without vegetation test would represent a situation where the global irrigation infrastructure map of *Siebert et al.* [2007] would suggest irrigation presence but very little NDVI would be present to support crop activity. Under these conditions the adjustment presented here would boost NPP regardless of actual crop production. It is possible that these locations exist around the world, for example in areas of subsistence agriculture, where small cultivated (high NDVI) and uncultivated (low NDVI) fields form a mosaic on the landscape resulting in small, observed NDVI. In contrast, consider a second location with moderate vegetation activity (e.g., NDVI of 0.65), depicting a managed agricultural site. When water stress is present, predicted NPP is low (140 gC/m^2/yr) regardless of the high vegetation activity observed by NDVI. When water limitation is completely removed, calculated NPP increases to over 1,400 gC/m$_2$/yr. This large contrast points to the importance of water limitation in global productivity models driven by satellite observations of NDVI. More specifically, in locations where irrigation is present, including environmental stresses in calculations will improve NPP estimates significantly. Without irrigation-based removal of natural meteorological stresses in dry areas, NPP predictions will necessarily be low, regardless of the high vegetation activity observed with NDVI [*Lobell et al.*, 2002]. The purpose of the water stress term adjustment presented here is to account for this stress factor.

[15] To assess the sensitivity of NPP to water availability and nutrient (fertilizer) input as well as the choice of cultivar, a second test was conducted across a large moisture gradient in the United States using a mechanistic crop growth model.

Table 1. Data Sets Used in CASA Modeling of Cropland NPP

Data Set	Temporal Coverage	Spatial Resolution	Source
Climate	Monthly averages (1998–2002)	0.5° lat × 0.5° lon	*Mitchell and Jones* [2005]
Soil	Static	5 × 5 arc min	*FAO* [2002]
NDVI	Monthly averages (1998–2002)	8 × 8 km	*Tucker et al.* [2005]
Land cover	Static (2000)	1 × 1 km	*Hansen et al.* [2000]
Crop type	Static (~2000)	5 × 5 arc min	*Monfreda et al.* [2008]
Irrigated area	Static (~2000)	5 × 5 arc min	*Siebert et al.* [2007]
Irrigation water use	Static (~2000)	5 × 5 arc min	*Siebert and Döll* [2008]

The selected locations ranged from arid (annual average precipitation = 278 ± 101 mm) to temperate (average annual precipitation = 635 ± 118 mm) to humid (annual average precipitation = 1055 ± 126 mm). The results from this analysis comparing the effects of fertilizer and irrigation for two crops, namely soybeans (a C3 crop) and maize (a C4 crop) indicated that irrigation has a larger impact in the arid west than in the humid east. The magnitude of change was on the order of 1000 percent. In contrast, the fertilizer effect was smaller, by 2 orders of magnitude, when compared to the irrigation effect. Similar to irrigation, the fertilizer effect was more pronounced in the arid experiment than in the humid location. The C4 crops responded more to synthetic nitrogen fertilizer than do C3 crops (which is expected considering the use of cultivars), but in all three cases, the irrigation effect was 3 orders of magnitude larger than the fertilizer effect regardless of the crop type in question. When both irrigation and fertilizer input were considered, the C4 crops yielded higher productivity than C3 crops (which showed no difference at all) in all three locations and the magnitude of increase was inversely related to the moisture status of a location. In the arid site, the C4 crops produced 13 percent larger NPP when both irrigation and fertilizer inputs were provided while in the humid site this difference was only 2 percent.

[16] In light of these sensitivity results, it is possible to conclude that water limitation is very important (at least as important as the other human factors) and the goal of this paper is to explore the magnitude of this effect by manually removing moisture limitation to production in locations known to be irrigated [*Siebert et al.*, 2007].

[17] Note that while a suite of new data sets [e.g., *Rost et al.*, 2008; *Portmann et al.*, 2010] have recently been available, the *Siebert et al.* [2007] data set remains the only global (reliable) digital map product that shows the location of irrigated areas ca. 2000. It was possible to use country-based irrigation efficiencies reported by *Rost et al.* [2008], this information is potentially even less reliable than the *Siebert et al.* [2007] data set. Considering the irrigation adjustment to maximum LUE based solely on area fractions rather than irrigation volumes, this study did not account for any irrigation efficiency reported by *Rost et al.* [2008].

[18] Also note that while irrigation can influence local temperatures through the process of evaporative cooling [*Lobell et al.*, 2008], this effect was not included in this study because of (1) the large grid size (~80 km^2) that is enough to mask this effect due to multiple land cover types being present (which occurs only on irrigated areas but not outside of irrigated areas) and (2) the reduction in air temperature due to irrigation dissipates quickly from leaf surfaces into the atmosphere and at two meters (which is the typical air temperature height used in this study) this effect would be lower.

2.3. Global Implementation

[19] Gridded model drivers for global cropland NPP estimates for the 1998–2002 period included (1) bimonthly NDVI data at 8 km resolution [*Tucker et al.*, 2005]; (2) global monthly observations of temperature, precipitation, and cloud cover at 0.5 degree grid resolution derived from interpolated weather station records distributed across the global land surface [*Mitchell and Jones*, 2005]; (3) the global soil texture data set [*IGBP-DIS*, 1998]; and (4) the global land cover data set of *Hansen et al.* [2000] at 1 km resolution using the University of Maryland (UMD) global classification scheme (Table 1). Downwelling shortwave radiation was derived from global solar radiation as a function of Earth-Sun geometry adjusted by sunshine hours [*Boland and Ridley*, 2008]. All spatial data sets were interpolated from their original spatial resolution onto a 5 min global grid (approximately 10 km at the equator). The CASA model was run from the steady state conditions following a spin-up process with 1998–2002 drivers and results from each year was averaged.

3. Results

[20] CASA-modeled global cropland NPP including irrigation effects averaged 650 gC/m^2/yr and ranged from 60 to 1,700 gC/m^2/yr. Globally, these values sum to ~7 PgC/yr, a value close to previously reported estimates for global cropland productivity including irrigated areas (5.4 PgC/yr [*Potter*, 1999]; 8.0 PgC/yr [*Field et al.*, 1998]; 9.2 PgC/yr [*Cramer et al.*, 1999]; and 8.0 PgC/yr [*Ito and Oikawa*, 2004]).

[21] At the site level, there is considerable agreement between modeled NPP from CASA and observed NPP at the sites considered in this study (Figure 2). The large discrepancy in the Nile Delta location largely stems from not accounting for multiple crops grown in a single year properly. While satellite derived fPAR (through NDVI) captured some of multiple cropping here, there could be up to four crops per year in the delta and their growth cycle may be less than the monthly available NDVI data and thus would not be fully accounted for. Note that even without the extensive multiple cropping present in field, the CASA model still predicts the highest NPP value here probably because of the availability of multiple-crop fPAR captured by remote sensing. Examination of a monthly NDVI time profile (not shown), in fact, suggests presence of maximum two growth cycles. At the

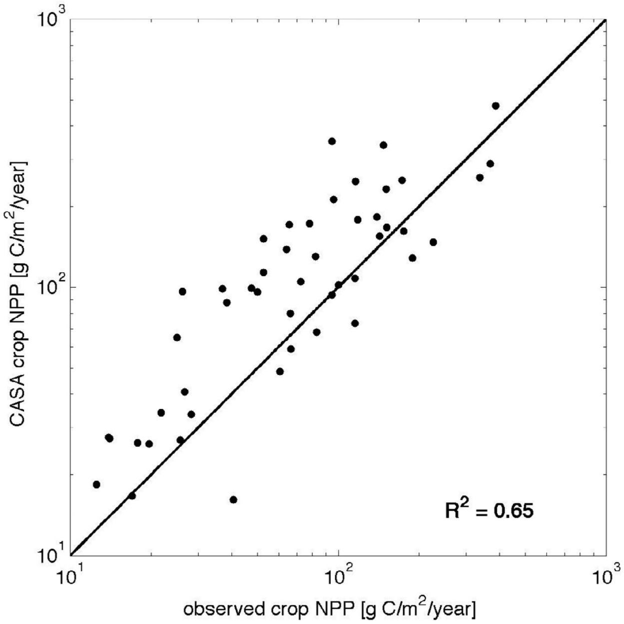

Figure 3. Comparison of average observed and modeled NPP for countries that have at least 10% irrigated area. The observed NPP data comes from *Monfreda et al.* [2008]. Note the log-log scale chosen to represent small and large averages equally. The regression based relationship is strong (R^2 value provided) and is statistically significant ($p < 0.0001$).

Harran site, the yields are reported at the district level, which includes both irrigated and some nonirrigated fields, and thus conversion of yields to NPP is reduced.

[22] CASA modeled NPP was also compared to ground-based NPP calculated from crop yields of *Monfreda et al.* [2008] for countries that have at least ten percent cropland irrigation (Figure 3). In general, there is a noticeable agreement between reported and modeled carbon fluxes, ranging from less than 100 g C/m^2/yr to in excess of 1,000 g C/m^2/yr. This comparison was made for all crops present in the country of interest.

[23] The spatial pattern of agricultural NPP follows that of global cropland distribution with a generally increasing trend from low- to high-precipitation availability except for intensely irrigated semiarid locations such as the Nile delta, central Spain, the western United States, northeastern China, northern India, and central Pakistan (Figure 4).

[24] Excluding the human factors including the decision to fertilize crops, availability and use of modern varieties optimized for irrigated/fertilized conditions, and politics/economics of irrigation systems that strongly influence global agricultural NPP, the CASA model predicts that removal of water limitation through irrigation has the potential to increase cropland NPP by an average of 25 gC/m^2/yr, which is roughly equal to 15 percent of average carbon uptake by global cropland areas (178 g C/m2/yr). The maximum productivity increase by irrigation could be as much as 627 gC/m^2/yr, which would suggest greater than 100 percent rise in productivity in heavily irrigated areas. Model-based

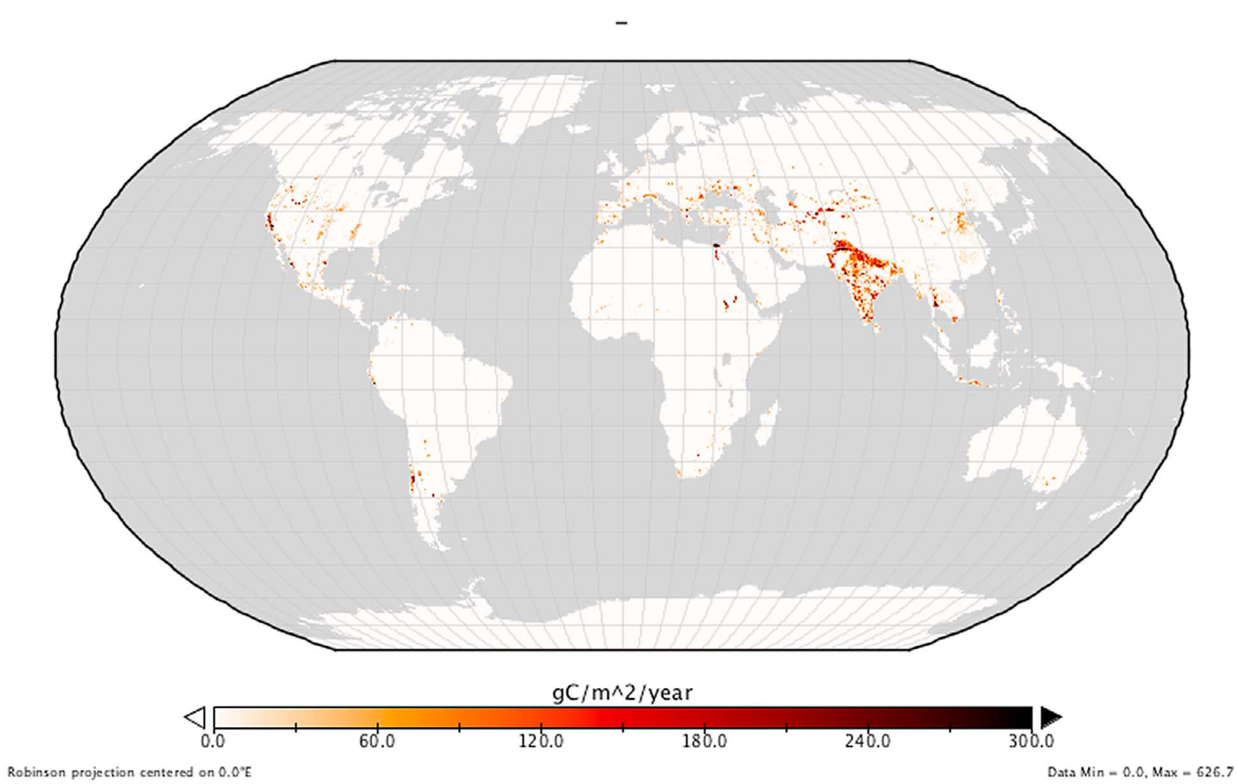

Figure 4. Global distribution and magnitude of changes in cropland NPP attributed to irrigation. The changes are the difference between NPP estimates from CASA runs with and without irrigation. The extreme values are cut off from this representation to show a better range.

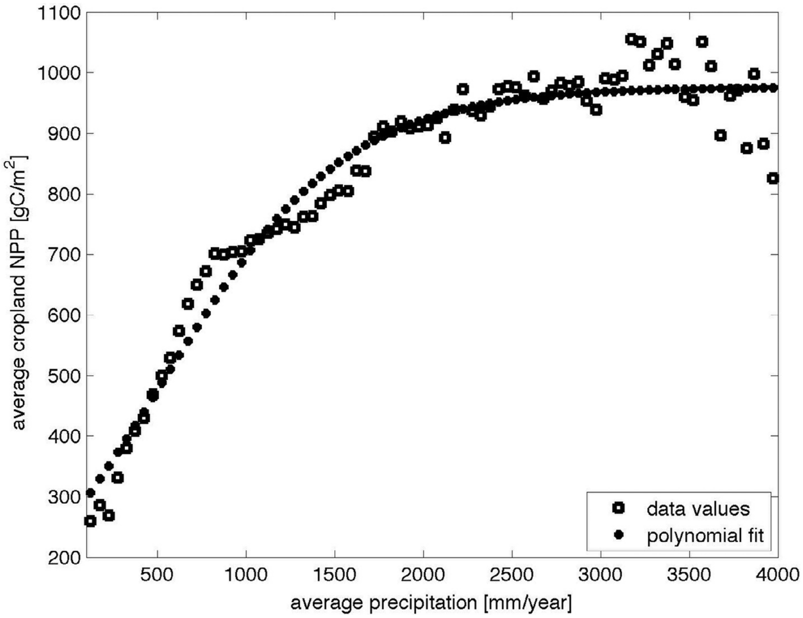

Figure 5. The relationship between modeled NPP and precipitation for grid points identified as croplands (squares). Each data point represents averaged binned response of NPP over small precipitation window. Also plotted is the best fit sigmoidal function determined from the data by minimizing least squared errors between precipitation and NPP. The form of the function is also provided.

assessment indicates that the largest changes in NPP occur in semiarid areas that receive substantial irrigation such as northern India, the Indus River Valley, northeast China, the western United States, and the Nile River Valley (Figure 4). In these locations, widespread use of irrigation would enable as well as elevate primary production in croplands by partially removing climatic constraints on productivity.

[25] Overall, the potential contribution of irrigation to global annual NPP — defined as productivity attributed to irrigation by removing water limitation alone — could exceed 0.4 PgC on average for the 1998–2002 period. This value is very close to other model or observation-based estimates of irrigated cropland NPP [e.g., *Cramer et al.*, 1999; *Ito and Oikawa*, 2004]. While small compared to global agricultural NPP (estimated to be 7–9 PgC [e.g., *Potter*, 1999; *Haberl et al.*, 2007]), this contribution approaches the total NPP of croplands in the United States (reported to be between 0.40 and 0.65 PgC [*Hicke et al.*, 2002; *Lobell et al.*, 2002]), which is a significant component of the annual carbon budget of the United States.

[26] This study also explored the depth of irrigation application required to increase NPP in the CASA model to better evaluate the NPP response to irrigation amounts. To do this, first the relationship between average annual precipitation and average annual cropland productivity without irrigation across a large moisture gradient was evaluated (Figure 5). When available moisture is below 1,500 mm/yr, productivity increases linearly. However, as precipitation increases beyond this value, the rate of NPP increase quickly diminishes and NPP saturates at around 1100 gC/m^2/yr, in line with observations of *Churkina et al.* [1999]. While this finding is not surprising given previous work on water limitation to productivity, it is useful to reiterate cropland response water in the context of this research.

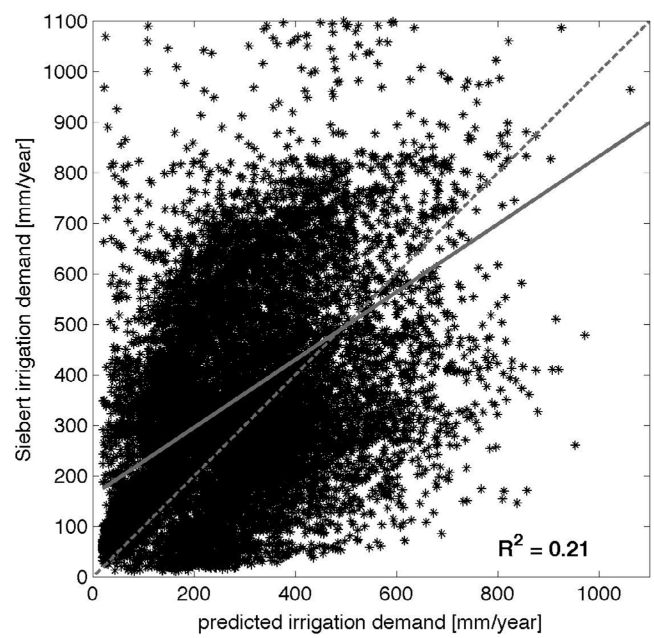

Figure 6. Comparison of predicted irrigation demand (x axis) computed as the amount of water needed to elevate cropland productivity to the level modeled by CASA when the irrigation module is activated to the irrigation demand computed independently by *Siebert and Döll* [2008]. Also included are the 1:1 line and the regression line calculated from a least squares estimate. While the relationship between the two estimates is weak, it is statistically significant ($p < 0.0001$).

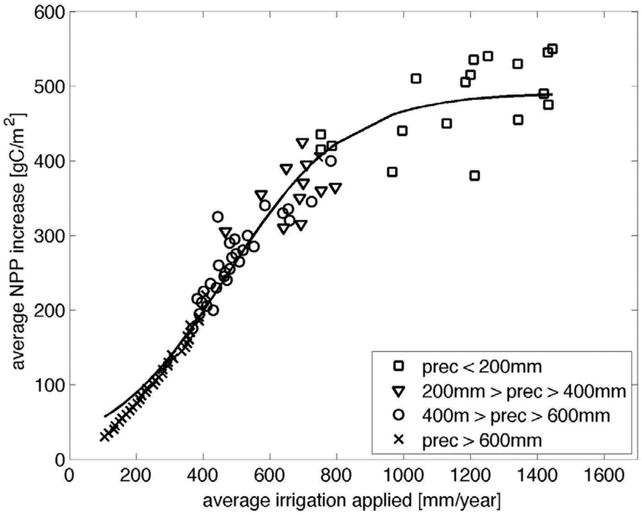

Figure 7. The relationship between average total annual irrigation water and average NPP increase estimated by CASA across four precipitation zones. Irrigation water data is estimated from CASA. The thick solid line is the sigmoidal best fit estimated via least squares (see text for details).

[27] To estimate irrigation water demand from CASA, a function that best described the relation between cropland NPP and precipitation was defined from the data plotted in Figure 5 by minimizing least squared errors between precipitation and NPP in the following form:

$$pred(NPP) = \frac{976.25}{1 + 2.7636\exp^{-0.0019PREC}} \tag{3}$$

where PREC is precipitation. This function (which is also plotted on Figure 5) was then translated back to demands for irrigation based on the observed changes in NPP between the control (nonirrigated) and irrigated CASA runs as a function of moisture availability. More specifically, the functional form of the relationship between moisture availability and NPP given in (3) was used to predict the amount of water that would be needed to elevate cropland productivity to the level modeled by CASA when the irrigation module was activated. The predicted amount of irrigation demand required to enable or raise NPP ranges from 50 to 1,500 mm/yr with a mean value of 500 mm/yr. To place this predicted irrigation demand into perspective, it was compared to the global irrigation water use data of *Siebert and Döll* [2008] in Figure 6. Despite the large scatter between the two estimates, there is a weak (R^2 value of 0.21) but statistically significant relationship between the two data sets even though they were computed completely independent of each other. Even though the points in Figure 6 relate to irrigated areas only, there are irrigation amounts close to zero (or very small). One explanation for the near zero values can be attributed to the very small irrigation amount predictions in data sets. Another possible explanation is the presence of supplementally irrigated areas (e.g., the East coast of the United States) with little irrigation need (which were not distinguished in the *Siebert and Döll* [2008] data).

[28] This research also explored the rate of NPP increases in the presence of irrigation as modeled by CASA (Figure 7). The primary difference between Figures 5 and 7 is that in the latter, average NPP increases due only to irrigation NPP is plotted instead of its absolute value. Note that in both plots, the water stress term already accounts for soil depth and soil texture. Examination of Figure 7 reveals that average annual NPP increase rises asymptotically with total available water (irrigation water data are from the CASA estimate). Data cover a large precipitation gradient, from less than 200 mm to greater than 600 mm. It is clear that the response of NPP to available water varies across precipitation regimes: in humid locations, NPP increases are small but steady; as aridity increases, irrigation input has a much bigger impact but begins to saturate as available water increases above 800 mm per year. Irrigation input in the humid zone increases NPP very little but in a consistent fashion, but in arid landscapes, irrigation has a large impact on NPP throughout and does not vary with the amount of irrigation input above 800 mm. Under dry conditions (precipitation <200 mm per year), NPP increase is dramatic but occurs as bulk increase.

[29] An additional interesting question regarding Figure 7 is: what is the relationship between total modeled NPP with total available water (irrigation + precipitation) for all the croplands? This relationship is shown in Figure 8 as a scatterplot. As with precipitation, cropland NPP response to total available water is asymptotic. Up to 1000 mm/yr of water availability, cropland productivity rises quickly, but beyond this point additional input of water results in increasingly diminishing returns to productivity. By fitting an empirical curve to this relationship (shown by the red line on Figure 8) it is possible to analyze the efficiency of irrigation globally and for different precipitation regions. The function itself is the locus of optimal production–irrigation points if water stress was the only factor limiting crop production. The form of this function is exponential and the coefficients of the function are provided on Figure 8. One interpretation of this relationship is that it resembles the well-known crop water production function, optimum value of which irrigation engineers around the world seek to attain the highest yield possible for the given irrigation inputs [*Brumbelow and Georgakakos*, 2007].

[30] In the histogram distribution of total available water for irrigated agriculture at global scales, the most frequently occurring amount of total available water is around 700 mm/yr, which could correspond to the most efficient production (i.e., highest returns per unit of water input) before productivity increase slows down. Note that the irrigation portion of the total available water in Figure 8 comes from an independent global estimate of *Siebert and Döll* [2008] for the analysis year (2000). Hence, this finding of irrigation efficiency at the most frequently observed water total may suggests that, at global scales, irrigators may have achieved the delicate balance between boosting crop productivity without wasting water. Of course this finding has to be interpreted in the context of other human factors that are not considered in this research and should be viewed with care.

4. Discussion

[31] A fundamental problem in global-scale studies of terrestrial carbon flux is that measurements at appropriate scale (i.e., at scales of grid points) rarely exist for any significant part of the globe. Therefore, direct validation of the global-scale model results is not possible/practical. This issue

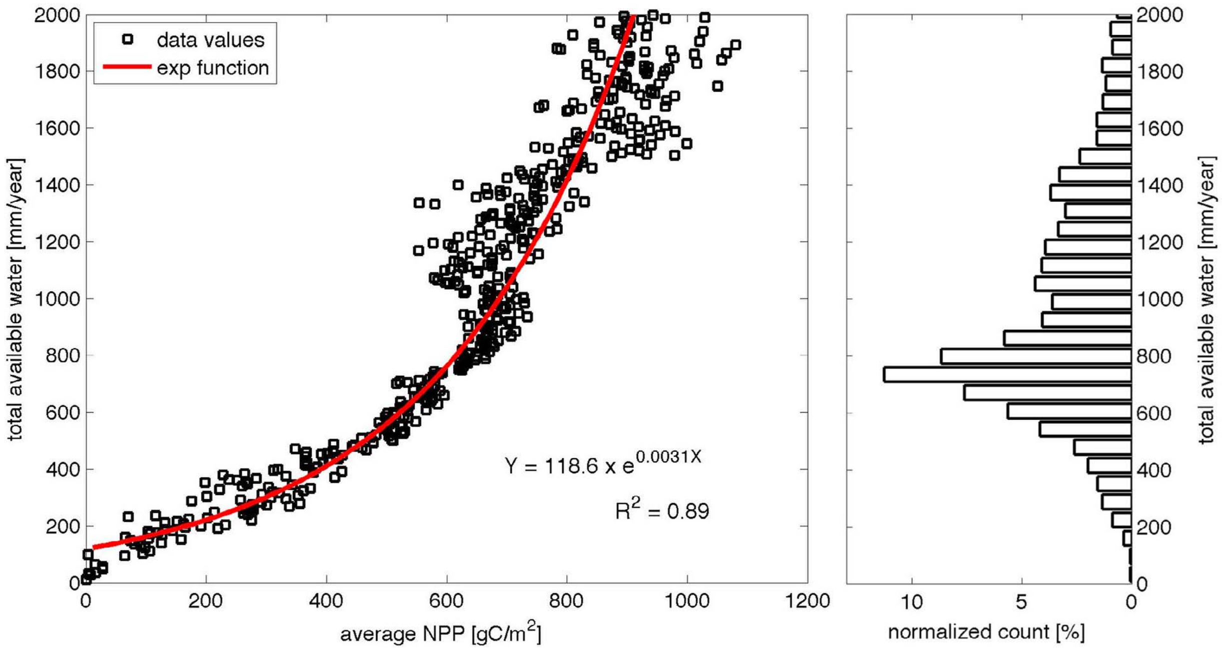

Figure 8. (left) The relationship between total available water and total NPP for all croplands showing the asymptotic relationship between the two variables. When total available water is less than 1000 mm, NPP increases linearly but above this point, the NPP increase per unit of water input slows down. (right) The histogram distribution of total available water (precipitation + irrigation) for croplands. The peak around 700 mm/yr may correspond to the most efficient production per unit of water input before further increase in productivity slows down.

of validation is further complicated by dearth of net biospheric carbon flux measurements made in cultivated areas, especially in irrigated croplands. In this research, an indirect validation method was chosen, where CASA-modeled NPP values in a few irrigated areas such as California, Mexico, India, and Turkey were compared to NPP data obtained by converting observed (reported) yields [e.g., *Monfreda et al.*, 2008]. This study, among others, points to two significant limitations concerning the quality of existing observed data sets as well as the compilation of point-based observations of biospheric carbon fluxes.

[32] The adjustment of LUE in section 2, based on observed NPP of *Monfreda et al.* [2008] yielded higher LUE in C4 crops than in C3 crops, a pattern also documented in previous studies [*Ruimy et al.*, 1994; *Gower et al.*, 1999; *Lobell et al.*, 2002]. However, even with the current adjustment to include irrigation effects, the LUE values reported here were generally lower than previously published LUE values. For example, based on an extensive review of published studies of LUE, *Gower et al.* [1999] reported a range of 2.85–5.07 gC MJ^{-1} PAR in C4 crops and 1.02–5.2 gC MJ^{-1} PAR in C3 crops. Similarly, *Ruimy et al.* [1994] calculated a value of 2.07 gC MJ^{-1} PAR for cultivated crops although that study did not distinguish crops with different photosynthetic pathways. A variety of factors may be contributing to this mismatch including the temporal scale, spatial scale, and the method with which LUE was quantified [*Bradford et al.*, 2005b]. For example, in the present research, LUE values were calculated from annual observations of NPP at a 5 min spatial grid scale, which includes nonvegetation areas. In contrast, many previous studies have quantified LUE for shorter time periods under laboratory conditions or at focused field sites. The method of estimation for *fPAR* and PAR may also be contributing to the observed differences. Here, monthly satellite-based observations of *fPAR* were used, which were originally derived from biweekly maximum value composites [*Los et al.*, 2000]. In contrast, high correlation between ground and satellite estimates of *fPAR* is only observed at seasonal scales [*Turner et al.*, 2002]. Finally, very often the values of LUE from local studies are given in g Dry Matter (and not g C). This is certainly the case for *Ruimy et al.* [1994], and possibly for others.

[33] In an ideal world, a model should never be validated with the same data that were used to calibrate it. However, in this paper the *Monfreda et al.* [2008] data were used in two very different ways that prevent this circularity from occurring. While the Monfreda et al. data were used to derive an empirical cropland LUE, it is important to clarify that these crop maps were used to develop two scalar values (irrigated versus nonirrigated) that were used as inputs to the CASA model. Moreover, these scalar values are not routinely adjusted by the model [e.g., *Potter et al.*, 2007]. The true drivers of the CASA model were the satellite derived NDVI data, the soil data, and the climate data. It is these variables that vary for each grid cell and directly influence the CASA model results for NPP. While this research returns to the spatially explicit and global cropland NPP data set of *Monfreda et al.* [2008] data set to assess the CASA model results, it was assumed that the *Monfreda et al.* [2008] data set was completely independent. This assumption was necessary

because there are simply no other global, spatially explicit data sets that could be used for comparison or validation of the model.

[34] In CASA, a portion of harvested crop NPP is not immediately returned to the soil and is assumed to be consumed locally and in the same season and is treated as a short-term recycling flux in agricultural settings [*Potter et al.*, 2007]. *Bradford et al.* [2005a] recently suggested that up to 17% of net primary production is removed from the U.S. Great Plains through harvest based on the assumption of 50% removal of crop residue. Assuming that this assumption holds globally, continuous biomass removals of this magnitude, especially in the presence of irrigation, at global scales could have substantial impacts on carbon storage and the long-term fertility of these ecosystems. Moreover, a recent work by *Ciais et al.* [2007] suggests that a large portion of biomass removed as harvest from croplands is laterally distributed through trade. Since the production of irrigated croplands is up to four times greater than nonirrigated lands, carbon associated with harvested and laterally transported crop products may be largely irrigation contributed. On the other hand, carbon extracted by crops from the atmosphere may be transferred to the soil through root production and residues following harvest, driving soil organic matter dynamics and net carbon balance, although this is not tested here. While these two contrasting views are location specific and dependent upon land use history, it may be safe to conclude that removing water limitation through irrigation in a model fundamentally alters the predicted carbon dynamics of agricultural lands.

[35] This study considers only water stress limitations to NPP. Hence other environmental controls (which themselves are interactive) such as nutrient availability, management, seed varieties, pests, weeds or biological constraints were not captured. The assumption is that other nutrient and biological limitations would be partially accounted for in the observed NDVI data; that is, higher greenness means more biomass, the productivity of which is then reduced by water and temperature limitations. The important contribution to draw from this research is that large-scale removal of water stress alters modeled global primary productivity and the information presented here provides a spatially explicit picture of the potential changes in cropland primary production affected by irrigation.

[36] The existing global NPP studies do not make full use of the available spatially explicit databases on crop types and agricultural management practices, partially because these data sets are just becoming available [e.g., *Portmann et al.*, 2010]. The study presented here integrates a calibrated terrestrial carbon model with publicly available global data sets on agricultural management practices to develop an assessment of global NPP modulated by only one aspect of human intervention, removal of water limitation, at fairly high spatial resolutions around the year 2000. Such modeling exercises that provide geographically referenced NPP and their corresponding seasonal fluctuations are vital to our understanding of both the functioning of ecosystems on which humans depend and their subsequent feedbacks to the environment even though they may not be capturing all factors that primary productivity depend on.

[37] In its current configuration, CASA model predicts primary productivity even in locations with severe water stress such as in the central valley of California. This occurs primarily because of the availability of potential for PAR absorption (*fPAR*) extracted from remote sensing. While this is not necessarily the case in the real world, it is an inherent limitation in models that combine remote sensing and terrestrial biogeochemistry. The advantage is that the NPP increase due to irrigation in CASA model is most pronounced in crop locations with severe water stress. In other words, even though CASA may inaccurately portray production in severely water stressed areas, the production increase is also most dramatic in these locations. This may be used as a proxy for areas where crops would not be grown at all without irrigation.

[38] The current approach models irrigation impacts only through the removal of moisture stress on light use efficiency. For example, there are many other human factors including the decision to fertilize crops, availability and use of modern varieties optimized for irrigated/fertilized conditions, and politics/economics of irrigation systems that strongly influence global agricultural NPP, but none were considered in this study. Given these limitations, the research presented here should be viewed as a modeling exploration with the help of an ecological model to better understand the controls on global crop productivity from irrigation.

[39] While a case can be made for irrigation impacts on leaf area index (LAI) and light absorption (i.e., LAI and light absorption are generally higher in irrigated lands), CASA's use of remotely sensed inputs such as NDVI to derive *LAI* and *fPAR* already accounts for observed increases in LAI and light absorption in these locations. More specifically, CASA loads water stress and nutrient variability on *APAR* as an observed variable and reduces productivity based only on reductions in LUE through moisture and temperature down-regulators. To justify this implicit assumption, *fPAR* in rain-fed areas was compared (not shown) to values in irrigated agricultural areas, which were defined as having greater or less than 50 percent irrigation in the *Siebert et al.* [2007] data set. In general, irrigated lands exhibit higher PAR absorption potential due to reduced water limitation and therefore it is assumed that this enhanced PAR absorption capability is captured by remotely sensed observations.

[40] One outcome of this study is that irrigation has an important role in boosting primary productivity of croplands in water limited areas. However, in the absence of good management practices, irrigation also has the potential to severely degrade the soil and water quality through waterlogging and soil salinization, and quantity through groundwater depletion. These forms of land and water degradation could have severe consequences for increasing crop yields with further concerns for income and employment in the long run. For example, large parts of formerly productive irrigated areas in India, China, and the United States are being abandoned due to deteriorating soil and water quality [*Singh and Pal Singh*, 1995]. So, while irrigation has the potential to substantially improve crop yields in arid and semiarid regions, these improvements may be eclipsed by degradation of resources that make cultivation possible in the first place. Therefore, irrigation along with good management practices

is required to globally sustain and increase crop productivity in the coming decades.

5. Conclusions

[41] Using a terrestrial ecosystem model that is modified for simulating agricultural management practices by removing water limitation to production, the potential contribution of irrigation to global agricultural NPP was estimated for the 1998–2002 period. Results show that by removing climatic constraints to productivity, irrigation has the capacity to increase cropland NPP in intensely irrigated areas by an average of 25 gC/m^2/yr with a maximum value of 627 gC/m^2/yr. Compared to the globally averaged carbon flux of 178 g C/m^2/yr, removal of water limitation makes an important contribution to cropland NPP at global scales. Overall, irrigation could elevate carbon uptake by the terrestrial biosphere by an additional 0.4 Pg, a value approaching the total NPP of U.S. croplands (estimated to be between 0.4 and 0.65 Pg). Considering the magnitude of this contribution, the results presented here underscore the need for incorporating agricultural management practices in models of the global carbon cycle.

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