Agricultural intensification and global environmental change

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Abstract

Intensification of agricultural management has allowed substantial increases in food production on existing agricultural lands, but with major global environmental costs. This dissertation explores the global-scale possibilities and tradeoffs associated with agricultural intensification using spatial data analysis and modeling. In Chapter 2, we analyze intensification opportunities from closing yield gaps, and find that large production increases (45% to 70% for most crops) are possible. We also examine what changes to management practices may be necessary to close these yield gaps, and find these vary considerably by region and current management intensity. A sub-national, crop-specific dataset of cropland nutrient use was developed to support this analysis. Chapter 3 focuses on intensification potential in the context of climate change. We find that a moderate yield gap closure scenario could result in net yield increases across much of the globe, even in the context of circa 2050 climate change. However, the capacity for intensification to overcome climate impacts erodes considerably under uniform global temperature increases of 4-5°C. Chapter 4 examines the opportunity space for improved nitrogen (N) management. We find that a reallocation of spatial N use intensity could achieve current cereal production with ~50% less N application and ~60% less excess N. We quantify a tradeoff frontier for nitrogen use and cereal production, and discuss the potential for efficiency improvements to push the frontier forward. This dissertation highlights the importance of improving agricultural management across the globe to meet food security and environmental goals.
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Chapter 1: Introduction

Meeting food demand while preserving natural ecosystems and protecting environmental quality is a grand challenge for society (Tilman et al. 2002, Godfray et al. 2010, Foley et al. 2011, Tilman et al. 2011). Food demand is projected to roughly double between over the next 50 years (Tilman et al. 2011) as population increases by another two and half billion people (United Nations Department of Economic and Social Affairs 2010) and per-capita dietary demands in the developing world are increasing with the adoption of increasingly meat-intensive diets (Kearney 2010, Tilman et al. 2011). This challenge will have to be met in a world that is undergoing rapid environmental change, of which agriculture a major driver (Foley et al. 2005, 2011).

Continued “intensification” of global agriculture – the ability to produce more food on a given plot of land – is generally seen as a necessary step towards meeting the joint food and environment challenge (Cassman 1999, West et al. 2010, Foley et al. 2011, Tilman et al. 2011, Bommarco et al. 2012). Intensification of croplands began in earnest during the Green Revolution, beginning with the advent of input-responsive hybrid dwarf wheat varieties developed by Norman Borlaug and others in the 1960s. The increase in food production brought about by the Green Revolution is thought to have been a humanitarian success, lowering food prices and helping overcome chronic food shortages in many developing nations (Pingali 2012).
Along with humanitarian benefits, intensification “spares” natural ecosystems from conversion to agriculture, a particularly important environmental benefit given that cropland and pasture systems already replace natural ecosystems across nearly 40% of earth’s ice-free land (Foley et al. 2011). The land sparing effect of intensification is mediated by economic factors, and may not necessarily occur in the same region as the intensification (Lobell et al. 2013b). Intensification can also lead to lower prices and thus stimulate demand increases, even potentially driving local land-use change. However, even with these factors taken into account, historical intensification has avoided a doubling of the cropland land area since 1961 and roughly 2 Gt of carbon emissions per year from land clearing (Burney et al. 2010).

While the land sparing effects of the Green Revolution were environmentally beneficial, the changes to agricultural management that accompanied Green Revolution yield increases have also driven large-scale environmental degradation. Water quality is degraded by overuse of nitrogen and phosphorus, which can cause health damages and decrease ecosystem services delivered by aquatic ecosystems (Keeler et al. 2012, Sutton et al. 2013). Climate warming and stratospheric ozone depletion are caused by the release of nitrous oxide (N₂O) from fertilized soils (Ravishankara et al. 2009, Sutton et al. 2013). While irrigated agriculture produces a disproportionate amount of global calories (Foley et al. 2011), unsustainably high rates of water use for irrigation stress water supplies in many regions (Tilman et al. 2002). Soil degradation and use of toxic chemicals for pest and weed control are also major environmental concerns (Tilman et al. 2002).

Given the complexities and multiple outcomes associated with agricultural intensification, this dissertation seeks to better understand the role of
intensification in meeting our food and environment challenges. Common themes running throughout the dissertation include a focus on analyzing spatial patterns and quantifying environmental tradeoffs. All analyses are carried out using spatial data at the global scale, in order to shed light on both global questions and regional context.

Chapter 2 analyses how cropland intensification through closing “yield gaps” (differences between observed crop yields and those attainable in a given region) would impact food production and agricultural management. To undertake this analysis, I developed a new global dataset of nitrogen, phosphorus, and potash fertilizer application rates by crop. Using this new dataset, we find that the spatial patterns of yield are heavily controlled by fertilizer use, irrigation, and climate. Input-yield models are developed to estimate which management practices are limiting yield increases in different regions and what changes to management practices may be necessary to close yield gaps. This chapter was published in *Nature* in October of 2012, and was co-authored by Jamie Gerber, Matt Johnston, Deepak Ray, Navin Ramankutty, and Jonathan Foley.

Chapter 3 examines the effects of the two most important trends affecting the future of global agricultural production: continued agricultural intensification and accelerating climate change. Many climate change-crop yield assessments consider only small tweaks to management, ignoring the decades-long trend towards intensification and increasing crop yields. Here we explicitly examine both factors, and provide global, spatial estimates of yield changes across the globe under multiple scenarios. We show that much of the world’s cropland has the capacity to achieve net yield increases with intensification even in the face of near-term (circa 2050) climate change. However, as temperatures increase to ~4-5°C, this “intensification capacity” erodes considerably. We find net decreases
in global production for maize, rice, and soybean under a uniform temperature increase of 5°C, even when considering a fairly aggressive intensification scenario. This chapter is currently in review for publication, and was co-authored by Jamie Gerber, Deepak Ray, Navin Ramankutty, and Jonathan Foley.

Chapter 4 quantifies a global tradeoff frontier for major cereal production and nitrogen use, using climate-specific nitrogen-yield response curves developed in Chapter 2. We find substantial opportunities exist to both simultaneously increase production and decrease excess reactive nitrogen released to the environment. These changes would require efforts to “balance” the geographic intensity of nitrogen use across the globe, in addition to improving nitrogen use efficiency. This chapter is being readied for publication, and includes contributions from Paul West, Jamie Gerber, Graham MacDonald, Steve Polasky, and Jonathan Foley.
Chapter 2: Closing yield gaps through nutrient and water management

In the coming decades, a critical challenge for humanity will be meeting future food demands without further undermining the integrity of the earth’s environmental systems (Cassman et al. 2003, Robertson and Swinton 2005, Royal Society 2009, Godfray et al. 2010, Foley et al. 2011, Tilman et al. 2011). Agricultural systems are already major forces of global environmental degradation (Foley et al. 2005, 2011), yet population growth and increasing consumption of calorie- and meat-intensive diets are expected to roughly double human food demand by 2050 (Tilman et al. 2011). Responding to these pressures, there is increasing focus on “sustainable intensification” as a means to increase yields on underperforming landscapes while simultaneously decreasing the environmental impacts of agricultural systems (Cassman 1999, Matson and Vitousek 2006, Royal Society 2009, Burney et al. 2010, Clough et al. 2011, Foley et al. 2011, Tilman et al. 2011). However, it is unclear what such efforts might entail for the future of global agricultural landscapes. Here we present a global-scale assessment of intensification prospects from closing yield gaps, the spatial patterns of agricultural management practices and yield limitation across the world, and the management changes that may be necessary to achieve increased yields. We find global yield variability is heavily controlled by fertilizer use, irrigation, and climate. Large production increases (45% to 70% for most crops) are possible from closing yield gaps to 100% of attainable yields, with changes in management practices needed to close yield gaps varying considerably by region and current intensity. Furthermore, we find there are large
opportunities to decrease the environmental impact of agriculture by eliminating nutrient overuse, while still allowing a ~30% increase in major cereal production. Meeting the food security and sustainability challenges of the coming decades is possible, but will require considerable changes in nutrient and water management.

**Main Text**

Opportunities for agricultural intensification were analyzed for seventeen major crops (which covered ~76% of global harvested cropland area between 1997-2003 (FAOSTAT 2012)). Yield gaps (Figure 2-1) were estimated by comparing landscape-level observed yields (Monfreda et al. 2008) to “attainable yields” (AYs), determined by identifying high-yielding areas within zones of similar climate. As empirical estimates, attainable yields are more conservative than absolute biophysical “potential” yields (Lobell et al. 2009), but they are likely achievable using current technology and management techniques.

Considerable yield improvement opportunities exist relative to current attainable yield ceilings, with opportunities differing dramatically by crop and geography (regional and country-specific data for all seventeen crops are summarized in the SI). Globally we find that closing yield gaps to 100% of AYs could increase worldwide crop production by 45% to 70% for most major crops (with 64%, 71%, and 47% increases respectively for maize, wheat, and rice). Eastern Europe and Sub-Saharan Africa show considerable “low-hanging” intensification opportunities for major cereals (Figure 2-2); these areas could see large production gains if yields were increased to only 50% of AYs. East and South Asia also have
Figure 2-1. Average yield gaps for maize, wheat, and rice. These were measured as a percentage of the attainable yield achieved circa the year 2000. Yield gap in each grid cell is calculated as an area-weighted average across the crops and is displayed on the top 98% of growing area.

Figure 2-2. Global production increases for maize, wheat and rice from closing yield gaps to 50%, 75%, 90% and 100% of attainable yields. The greatest opportunities for increases in absolute production (from closing yield gaps to 100% of estimated attainable yields) are wheat (W) in Eastern Europe and Central Asia, rice (R) in South Asia and maize (M) in East Asia. Absolute production increases for individual crops in Sub-Saharan Africa are smaller owing to lower attainable yields and diverse cropping systems (that is, less area devoted to any one crop). The region could still achieve large production increases in cassava, maize and sugarcane.
substantial intensification opportunities due to their vast agricultural lands and geographic variability in yield and yield gaps.

Assessing opportunities for more sustainable intensification requires an understanding of the factors driving yield variation across the world. Fundamentally, yield gaps are caused by deficiencies in the biophysical crop growth environment that are not addressed by agricultural management practices. Here we explicitly examined key biophysical drivers of crop yield by using global, crop-specific irrigation data (Portmann et al. 2010) and by developing a new global, crop-specific dataset of nitrogen (N), phosphate (P$_2$O$_5$), and potash (K$_2$O) fertilizer application rates. We find extensive geographic variation in these management practices, with high fertilizer application rates concentrated in high-income and some rapidly developing countries (Figure 2-3a, Figure 2-S1). Likewise, irrigated areas (Portmann et al. 2010) are heavily concentrated in South Asia, East Asia, and parts of the United States (Figure 2-3b).

Building input-yield crop models, we found that the spatial patterns of climate, fertilizer application, and irrigated area explain 60-80% of global yield variability for most major crops (SI, Table 2-S1). Yields of some crops (e.g. sorghum, millet, and groundnut) were primarily controlled by climate, while others (e.g. barley, sugar beet, and oil palm) showed strong management responses. Surprisingly, model residuals showed little sensitivity to soil and slope parameters (SI, Figure 2-S2), suggesting that such relationships are obscured at the landscape scale with existing datasets.

The factors that primarily limit increasing crop yields to within 75% of their AYs (Figure 2-4, Figure 2-S3) vary by crop and region. For example, Eastern Europe
Management intensity of nitrogen fertilizer and irrigated area varies widely across the world's croplands. a) Fertilizer and irrigation values are area-weighted averages across major cereals.

**Figure 2-3.** Management intensity of nitrogen fertilizer and irrigated area varies widely across the world's croplands. a) Fertilizer and irrigation values are area-weighted averages across major cereals.
and West Africa stand out as hotspots of nutrient limitation for maize, while Eastern Europe appears to experience nutrient limitation for wheat. Co-limitation of nutrients and water is observed across East Africa and Western India for maize, portions of the US Great Plains and the Mediterranean Basin for wheat, and in Southeast Asia for rice. We note that the management practices limiting yield increases depends on the degree of yield gap closure desired (Figure 2-S4). For example, closing maize yield gaps to 50% of AYs (~2.3 t/ha) in Sub-Saharan Africa primarily requires addressing nutrient deficiencies (Figure 2-S4a), but closing yield gaps to 75% of AYs (~3.5 t/ha) requires increases in both irrigated area and nutrient application over most of the region (Figure 2-4a). We project potential changes in irrigated area and nutrient application needed to close yield gaps on maize, wheat, and rice to within 75% AYs (a 29% global production increase) utilizing our input-yield models. At the landscape scale, yield gaps in co-limited regions can be closed via a range of irrigated area and nutrient intensity combinations (e.g. Figure 2-S5). For example, 73% of these underachieving areas could close yield gaps by solely focusing on nutrient inputs (with 18%, 16%, and 35% increases in N, P₂O₅, and K₂O application relative to baseline global consumption, respectively), while only 16% of underachieving areas could close yield gaps by solely increasing irrigation. Jointly increasing irrigated area and nutrient application could close yield gaps on all underachieving areas (with 30%, 27%, and 54% increases in N, P₂O₅, and K₂O application and a 25% increase in irrigated hectares).

To minimize the environmental impacts of intensification, increased irrigation and nutrients to close crop yield gaps should be complemented by efforts to decrease overuse of crop inputs wherever possible (Ju et al. 2009, Vitousek et al. 2009, Liu et al. 2010, MacDonald et al. 2011a); combined, these efforts could increase total food production while decreasing the overall global use of water and
Management factors limiting yield-gap closure to 75% of attainable yields for maize, wheat and rice. Yield-limiting management factors for a) maize, b) wheat, and c) rice were calculated using the suite of input–yield models, comparing current input intensity against estimated required levels to close yield gaps.

Figure 2-4.
nutrients. For example, we estimate that by addressing imbalances and inefficiencies, nitrogen and phosphate fertilizer application on maize, wheat, and rice could decrease globally by 11 million tons of nitrogen (28%) and 5 million tons of phosphate (38%) without impacting current yields (Figure 2-S6). Nutrient overuse on these crops is particularly dramatic in China, confirming field-scale results (Ju et al. 2009). To close yield gaps to 75% AYs while also eliminating input overuse (under joint nutrient and irrigation intervention), we project smaller net changes in nutrient inputs would be required: 9%, -2%, and 34% changes in N, P₂O₅, and K₂O application (Figure 2-5, Figure 2-S7). Notably, it would be possible to close global yield gaps on major cereals to within 75% of AYs with fairly minimal changes to total worldwide nitrogen and phosphate use by coupling targeted intensification with efforts to reduce nutrient imbalances and inefficiencies. Geographically optimizing input intensity and increasing field-scale efficiencies could further improve production relative to inputs.

Closing yield gaps may not always be desirable or practical in the short-term given marginal returns for additional inputs, regional land management policies, limits on sustainable water resources, and socio-economic constraints (e.g. access to capital, infrastructure, institutions, and political stability). Use of precision agriculture techniques, conservation tillage, high-yielding hybrids, increased plant population, and multifunctional landscape management can help mitigate negative environmental impacts of intensive agriculture (Cassman et al. 2002, Oenema and Pietrzak 2002, Jordan et al. 2007). Additionally, use of organic fertilizers (omitted in this analysis due to data limitations) are essential for improving soil carbon, enhancing soil biota, and increasing water-holding capacity (Sanchez 2010). Social triggers of intensification will differ across regions: development interventions by governments or NGOs, market-driven incentives for farmer investment, and land scarcity in regions not fully connected
Figure 2-5. Closing yield gaps through changes in agricultural management. a) Projected increases in nitrogen application rates and b) irrigated areas necessary to close maize, wheat and rice yield gaps to 75% of attainable yields. c) Projected net changes in nitrogen application rates when closing yield gaps and eliminating input imbalances and inefficiencies.
to global markets (Lambin et al. 2001). Changes to agricultural management to 
close yield gaps should be considered in the context of climate change, which is 
expected to substantially impact yields (Parry et al. 2007, Lobell et al. 2011a) and 
induce management adaptations (Howden et al. 2007). Specifically, a major 
concern is how changes in water availability may conflict with projected irrigation 
requirements for closing yield gaps.

The fertilizer dataset, yield gap estimates, and yield models presented here could 
be widely used to assess intensification opportunities and the environmental 
impacts of changing agricultural systems. However, these data and analyses are 
not without limitations (full discussion in SI). Most importantly, the analyses rely 
on agricultural management, yield, and climate data from a variety of different 
sources and scales. Overall, these results are most useful across regional and 
global scales, leaving fine-scale and temporal details obscured (e.g. intra- and 
inter-annual variation in climate and yield creates particular uncertainty 
surrounding irrigation requirements). Moreover, while our models confirm the 
importance of climate, fertilizers, and irrigation in determining contemporary 
patterns of global cropland productivity, we do not discount the importance of 
additional biophysical characteristics (including soil characteristics, see SI) and 
management practices (including crop rotation patterns, organic nutrient inputs, 
micronutrients, improved seed quality, conservation tillage, and pest 
management). Incorporating these factors into the analytical framework could 
improve the accuracy and utility of the analyses. Additional research on cropland 
intensification must also assess the opportunities and environmental tradeoffs for 
increasing cropping intensity and decreasing pre- and post-harvest crop losses.

The future of agriculture faces a dual grand challenge: significant increases in 
food demand must be met while decreasing agriculture’s global environmental
footprint. Closing yield gaps and increasing resource efficiency are necessary strategies towards meeting this challenge, but they must also be combined with efforts to produce advanced crop varieties, halt agricultural expansion, reduce food waste, and promote sensible diets (Godfray et al. 2010, Foley et al. 2011). This analysis emphasizes the critical role of nutrient and water management in pathways towards sustainable intensification and provides a starting point for a more comprehensive discussion of intensification opportunities and challenges. Context-dependent policies and agricultural development programs must address drivers of yield limitation while encouraging management practices that improve tradeoffs between production and environmental impacts.

Methods Summary

Yield gaps were quantified by comparing existing yields to climate-specific attainable yields. Our approach refines previous estimates (Licker et al. 2010, Johnston et al. 2011) by excluding climate outliers and utilizing crop-specific, equal-area climate zones.

Fertilizer application rate and consumption data were compiled for nations and subnational units across the globe (Table 2-S2). Application rates for crop-country combinations missing data were estimated as described in the SI. Crop- and crop group-specific application rates were then distributed across detailed maps of crop (Monfreda et al. 2008) and pasture (Ramankutty et al. 2008) areas, and rates were harmonized with subnational and national nutrient consumption data.

Fertilizer and irrigation data were used to parameterize nutrient response curves and rainfed maximum yields, using nonlinear regression analyses within each
climate zone. Utilizing these relationships, we estimated changes in inputs necessary to close yield gaps, as well as decreases in inputs possible from addressing inefficiencies and imbalances.
Supplementary Information – Methods

Mapping agricultural management: A global dataset of crop-specific nitrogen, phosphate, and potash fertilizer application rates and consumption

To develop our crop-specific dataset of nitrogenous, phosphate, and potash fertilizer application for 138 crops and pasture, we used a spatial disaggregation method building on the work of Potter et al. (Potter et al. 2010) to fuse both national and, where available, sub-national data from a variety of sources (Table 2-S2).

Data collection

We collected national and sub-national data on fertilizer application rates for crops and crop groupings. A major source of data was the fifth edition of “Fertilizer Use by Crop” (hereafter referred to as the FUBC5 dataset), a joint publication from the International Fertilizer Industry Association (IFA), the International Fertilizer Development Center (IFDC), the International Potash Institute (IPI), the Phosphate and Potash Institute (PPI), and the Food and Agriculture Organization of the United Nations (FAO) (IFA IFDC IPI PPI FAO 2002). The publication contains national-level application rate data by crop for 42 countries, compiled from the following data sources: FAO questionnaires given to member countries; IFA questionnaires given to industry companies, research institutes, and fertilizer associations; IFDC questionnaires sent to experts attending courses, seminars, and professional meetings; and IPI and PPI
communications with experts. Most of the application rate data from the FUBC5 dataset are for the years 1999 or 2000, but data for some countries are as old as 1994 and as recent as 2001.

To expand spatial and sub-national data coverage, we also collected data from national statistical bureaus, FAO reports, and national-level fertilizer industry associations (see later sections for more description on how these datasets were compiled and harmonized). Following Monfreda et al. (Monfreda et al. 2008), we established a 7-year data collection window centered on the year 2000 (1997-2003). We calculated averages for countries when data for multiple years was available within this window. When countries did not have data available within our desired timeframe (as was the case for some countries in the FUBC5 dataset), we used data from the year closest to our data collection window. For some countries, the only fertilizer information available was FAO nutrient consumption data (FAOSTAT 2012), which we collected for all countries available. Data sources are listed in Table S2. Sub-national data was all provided at the state/province-level, except for the US AAPFCO data (Association of American Plant Food Control Officials 2002), which we aggregated from the county-level to the state-level for consistency. The countries for which we compiled sub-national data represent 45%, 50%, and 55% of total global N, P_2O_5, and K_2O consumption, respectively (FAO nutrient consumption from 1997-2003).

We next identified “data gaps” for each crop category: countries where we had crop areas but no fertilizer application rate data in our database. As fertilizer use is highly correlated to income-level (Tilman 2001), we chose to use an income-based extrapolation technique to fill these data gaps. Countries were grouped into four economic aggregates based on the World Bank (World Bank 2010)
income classifications: low income, lower middle income, upper middle income, and high income (both OECD and non-OECD countries). For each crop, we calculated area-weighted average fertilizer application rates for each economic aggregate. We then identified the economic group of each country missing application rate data and filled gaps using the average application rates. The poorer data quality of extrapolated rates was noted accordingly in a data quality map corresponding to each crop.

For some crops, we lacked observational data on application rates from any country within a particular economic group. In these cases we calculated the area-weighted average application rate across the entire globe and utilized this rate to extrapolate to areas missing data. While clearly not ideal, having an application rate value for each crop, even if it is of low quality, allows us to scale the application rates to match total FAO nutrient consumption in a country. This allows us to gain a first-order approximation of the true application rate.

We collected fertilizer data (from either a crop-specific or crop-group-specific application rate) for 138 crops and pasture. No tabular fertilizer information in any country was available for some minor crops for which we did have harvested area data (the M3 crop area dataset contains data for 175 crops) (Monfreda et al. 2008). We disregarded these crops in our dataset and assumed negligible fertilizer consumption.

Mapping of application rate information

As with previous studies, our approach matches spatial data on agricultural land use with tabular application rate data for particular crops or crop groups. Potter et al. (Potter et al. 2010) linked cropland or crop-group maps from the M3 croplands
dataset (Monfreda et al. 2008) and the M3 pasture dataset (Ramankutty et al. 2008) to each national-level application rate data entry in the FUBC5 dataset. We used and revised the Potter et al. linkages, especially focusing on which Monfreda et al. datasets were used for crop groupings. For example, in Morocco, Potter et al. distributed FUBC5 application rate data for the category “oil crops, other” onto the Monfreda et al. crop map for “oilseeds, other”. Since the only oil crop with its own application rate data listed in the IFA/FAO/IFDC report is sunflower, we chose instead to distribute the fertilizer application rates for the “oil crops, other” category onto all the Monfreda et al. oil crop maps except sunflower (this includes not only the “oilseeds, other” category, but also soybeans, sesame seed, safflower seed, etc.). The same method was applied to identify constituent crops for all crop groups.

In most cases, national and sub-national fertilizer application rates from our data (Table 2-S2) were first directly applied to the appropriate crop maps. We modified the raw application rates at this step in three cases: 1) if a data source indicated that only a percentage of a particular cropland area was fertilized, 2) if the fertilized pasture area in a country was less than the pasture area for that country from the M3 pasture dataset, and 3) if we had data for seasonal varieties of barley and wheat. Below are the adjustments made for these three special cases:

1. Consistent with the Potter et al. (Potter et al. 2010) methodology, when only a percentage of a cropland area was fertilized we adjusted application rates downward by the same percentage. For example, the FUBC5 dataset indicates that 85% of Mexico’s avocados are fertilized at an average rate of 120 kg N/ha, so we
applied an application rate of 102 kg N/ha to all of Mexico’s avocado area.

2. Similar to case 1), in many cases only a percentage of pastureland in a country was fertilized. While this percentage was not explicit in the FUBC5 dataset, we calculated this number by comparing the FUBC5 fertilized pasture area with the total M3 pasture areas within each country (Ramankutty et al. 2008). For areas where the M3 pasture areas were greater than FUBC5 pasture areas, we reduced application rates by the proportion of FUBC5 pasture area to M3 pasture area (i.e. if FUBC5 listed half the pasture area contained in the M3 dataset, we reduced the FUBC5 pasture application rates by half).

3. For seasonal varieties of wheat and barley, we calculated average “wheat” and “barley” application rates, weighting the FUBC5 seasonal crop application rates by the FUBC5 seasonal crop areas.

Harmonize with FAO consumption dataset

To harmonize our dataset with 1997-2003 FAO national nutrient consumption data (10), we first calculated initial estimates for global consumption of N, P$_2$O$_5$, and K$_2$O by multiplying our crop application rate maps by M3 crop areas. We differentiated between “trusted crops” – crops for which we have sub-national or national-level application rate information – and “untrusted crops” – crops for which application rates were derived through the aforementioned extrapolation procedure. In most cases we trusted the application rates from our trusted crops, and thus we only scaled untrusted crop application rates up or down to match average FAO total national nutrient consumption (note that the same scalar was
applied to all untrusted crops). Two special cases led us to have less trust in our “trusted crop” consumption and we altered our scaling procedure:

1. When the scaling correction for untrusted crops required more than a doubling of those application rates within a country, we chose to scale the application rates of all crops to meet FAO consumption levels. In a few small countries, we also capped the scalar for all crops at a doubling of application rates. In these cases our data were not reconciling either due to underreporting of cropland area, crops missing from our dataset, or errors with either the application rate data or the FAO consumption data.

2. When the total fertilizer consumption summed over trusted crops alone already exceeded or nearly exceeded (>95%) the FAO consumption within a country, we adjusted the scaling procedure by scaling the application rates of all crops to match the FAO consumption. Again, this is another case where our multiple datasets were not reconciling due to one of the above possible complications.

No FAO consumption data was available for Gibraltar, Liechtenstein, Western Sahara, and 37 small island countries and territories. For these locations, consumption was recorded as “not a number”. Application rate data remained unscaled and was noted accordingly in the data quality map.

*Enhance sub-national resolution*

Sub-national consumption and aggregate application rate data, when available, was used to add spatial resolution to our national application rate data.
Consumption data came in three main forms: 1) total nutrient consumption in each sub-national unit, 2) fertilizer consumption by type (i.e. “nitrogenous” or “compound”) in each sub-national unit, and 3) average nutrient application rates (across all crops) in each sub-national unit. We multiplied average application rates by the number of potentially fertilized hectares (as defined by the sum of the crop proxy and pasture maps) to obtain nutrient consumption in each sub-national unit. Then, for all countries except the US, we harmonized the sum of the sub-national consumption data for each nutrient (including compound fertilizers when available) by scaling it to match the FAO national consumption data. In the US, sub-national consumption data was already listed in units of N, P$_2$O$_5$, and K$_2$O, but it could not be compared to FAO consumption because the data did not have national coverage. Due to this complication, we used the US sub-national consumption data directly without calibration to FAO.

Next, we added up consumption according to our application rate and area maps in each sub-national unit. Application rates for all crops, except those for which we had sub-national application rate data, were scaled so that the sum of all consumption in the sub-national unit matched the sub-national consumption data. Scalars were allowed to vary ±25%, since we observed that variation from the median rate commonly varied ±25% in countries where we had sub-national data. Sub-national application rates were not scaled using the sub-national consumption data.

The sub-national scaling cap of ±25% can slightly affect consistency with the FAO consumption dataset. Thus, for countries where we calculated and used sub-national consumption scalars, we once again scale all application rates – except those originally from sub-national data sources – to match FAO consumption data.
Record data quality

The quality of application rate data varies substantially across the globe due to the availability of input data. For example, an application rate may come directly from unaltered sub-national data, it could be a national-level application rate scaled by sub-national consumption data, an extrapolated rate from similar-income countries normalized to FAO consumption, etc. Thus, we recorded data quality in a data type map for each nutrient and crop combination that details the quality of the input data and the manipulations made (if any) to record or estimate fertilizer application rate at every location where that crop is cultivated. Data type is indicated in each map through a unique numerical code.

Calculating climate bins and yield gaps

To calculate attainable yields (AYs) and yield gaps for our 17 major crops (wheat, rice, maize, soybean, barley, sorghum, millet, cotton, rapeseed, groundnut, sunflower, sugarcane, potato, cassava, oil palm, rye, and sugar beet), we build on recently developed climate analog techniques (Licker et al. 2010, Johnston et al. 2011). Crop and climate data used in these analyses are all at the 5 arc-minute by 5 arc-minute resolution.

We calculate unique climate bins for each crop by establishing 100 zones of similar annual precipitation and growing degree-day (GDD) characteristics, where each of the 100 zones contains equal harvested area (see section “Comparison to previous yield gap analyses” for a discussion about using annual precipitation as the moisture variable). We use interpolated mean daily
temperatures from the WorldClim dataset (Hijmans et al. 2005) and crop-specific base temperatures from Licker et al. (Licker et al. 2010) to derive growing degree-days using methods described by Licker et al. (Licker et al. 2010). Mean annual precipitation (P) is directly derived from the WorldClim dataset (Hijmans et al. 2005).

Using these two variables, we discard grid cells that are climate outliers by defining a compact contour in precipitation-GDD space containing 95% of a crop’s harvested area (crop area and yield data is from Monfreda et al.) (Monfreda et al. 2008). This contour is derived in several steps. First, we define a 2-dimensional histogram of harvested area in a precipitation-GDD space with 300x300 bins. A smoothed distribution is then constructed by convolution of the 2-D histogram with a Gaussian distribution $G$, defined in Eqn. S1, where the smoothing lengths $L_P$ and $L_{GDD}$ are chosen as $1/10^{th}$ of the span of the crop-specific domain of precipitation and GDD values, respectively. $N$ equals the normalization constant.

$$G(GDD, P) = Ne\left(\frac{p^2 + \frac{GDD^2}{L_{GDD}^2}}{L_p^2 + L_{GDD}^2}\right) \quad (\text{Eqn. S1})$$

A contour is defined which includes 95% of the smoothed area distribution. If this step results in multiple contours, the smoothing convolution is recomputed with the smoothing lengths $L_P$ and $L_{GDD}$ 10% larger. This convolution is recalculated with progressively larger smoothing lengths until a single contour is found that contains 95% of the crop’s harvested area. This contour represents a climatic envelope in which we feel comfortable calculating attainable yields from our dataset. Attainable yields and intensification potential are only calculated for the grid cells characterized by climates within this climate envelope.
Once a contour is identified, we identify 10 zones along the GDD axis that each contain 10% of the remaining harvested area. Within each GDD zone, we divide the area into 10 equal-harvested-area precipitation bins. Continuing this method in each GDD zone results in 100 crop-specific equal-area bins with similar GDD and annual precipitation characteristics (Figure 2-S8).

Within each of the 100 bins, we analyze the yield distributions to determine AYs. We first temporarily discard the smallest-area grid cells (for a total of 5% of the bin area), in order to remove potential outliers from the yield dataset. An "attainable yield" is then defined as the area-weighted 95th percentile observed yield within a climate bin. Intensification potential (Figure 2-1, Figure 2-2) and average yields (online supplement) are defined as closing yield gaps in the worst performing regions up to different levels (50%, 75%, 90%, and 100%) of AYs.

Analyzing drivers of yield gaps

To analyze drivers of yield gaps, we used a nonlinear least-squares algorithm to fit input-response models to yield distributions within each climate bin for every crop.

Explanatory variables

Nitrogen, phosphate, and potash fertilizer application rates used as inputs for the models are directly from the fertilizer dataset developed in this study.

We calculate the maximum proportion of crop growing area irrigated in each grid cell in order to establish the spatial extent of irrigation technology and
infrastructure for each crop (this variable is listed as IRR in the equations below and mapped for major cereals in Figure 2-3b). We utilize the MIRCA2000 dataset (Portmann et al. 2010) for this calculation, which contains monthly rainfed and irrigated areas for our crops of interest. We restrict our search for maximum irrigated proportion to months for which the reported crop growing area is at least 75% of the maximum in order to exclude anomalous growing conditions (e.g. a small area of a particular crop may be cultivated beyond of the normal growing season and be 100% irrigated, but this would not reflect the extent of irrigation capacity within the main growing season when only 50% of the area is irrigated).

Model functional form

While debate exists about the ideal functional form for input-yield models, there is general agreement in limited substitutability between inputs and a yield plateau at high inputs. To calculate our empirically derived crop yield models, we use a nonlinear least-squares algorithm (trust region reflective) to fit input-response models to yield distributions within each climate bin. We utilize a standard functional form (Mitscherlich-Baule, Eqn. 2-S2) for yield response to nutrient (nitrogen, phosphate, and potash) application rates (Frank et al. 1990, Paris 1992). We follow the von Liebig “law of the minimum” (Paris 1992) to assess the combined effects of inputs. Thus, grid cell crop-specific yield ($Y_{modGC}$) is modeled as in Eqn. 2-S2 for 100% rainfed grid cells, where $Y_{max}$ is the maximum yield possible within the climate bin; $b_{NP}$ and $b_K$ describe the y-intercepts for each nutrient-yield response curve (the potash y-intercept is unique from the other nutrients as described in the parameters section below); $c_N$, $c_P$, and $c_K$ are response coefficients that describe the percent of $Y_{max}$ achieved at a given nutrient level; $N_{GC}$, $P_{GC}$, and $K_{GC}$ are kg/ha of N, P$_2$O$_5$, and K$_2$O fertilizer applied to the grid cell.
When grid cells contain a mixture of rainfed and irrigated areas, rainfed yields may be limited by nutrient application (as in Eqn. 2-S2) or a climate-specific rainfed yield maximum ($Y_{maxRF}$). When grid cell nutrient application rates exceed those required to achieve the rainfed yield maximum, we assume nutrients in excess of those required to achieve the rainfed yield maximum are applied preferentially to irrigated areas. For example, nitrogen requirements for the rainfed yield maximum ($N_{\text{reqRF}}$) are calculated as in Eqn. 2-S3 and nitrogen application rates for irrigated lands are calculated as in Eqn. 2-S4. Similar calculations are done for phosphate and potash.

\[
N_{\text{reqRF}} = -\ln\left(\frac{1-\left(\frac{Y_{\text{maxRF}}}{Y_{\text{max}}}\right)}{b_{NP}}\right)/c_N \quad \text{(Eqn. 2-S3)}
\]

\[
N_{\text{IRR}} = \frac{N_{GC-\left(N_{\text{reqRF}}(1-IRR)\right)}}{IRR} \quad \text{(Eqn. 2-S4)}
\]

Irrigated modeled yield is determined using the nutrient response curves and the nutrient application rates for irrigated area (Eqn. S5). Grid-cell modeled yield is then a simple weighted average of the maximum rainfed yield and the modeled yield on irrigated land (Eqn. S6).

\[
Y_{\text{modIRR}} = \min\left(Y_{\text{max}}\left(1 - b_{NP}e^{-c_NN_{\text{IRR}}}\right), Y_{\text{max}}\left(1 - b_{NP}e^{-c_PN_{\text{IRR}}}\right), Y_{\text{max}}\left(1 - b_Ke^{-c_KN_{\text{IRR}}}\right)\right) \quad \text{(Eqn. 2-S5)}
\]

\[
Y_{\text{modGC}} = \left(1 - \text{IRR}\right)Y_{\text{maxRF}} + \text{IRR} Y_{\text{modIRR}} \quad \text{(Eqn. 2-S6)}
\]
Parameters

We define $Y_{max}$ as the 98th percentile yield within a climate bin and $b_{NP}$ (which defines the y-intercept for the nitrogen and phosphorus curves) is calculated using the 2nd percentile yield within a climate bin. We do not use the maximum and minimum within each bin due to observed outliers within the dataset. The decision to define the y-intercept and yield maxima using climate bin yield information keeps the models grounded in the empirical data, reduces the dimensionality of the nonlinear fitting routine, and provides an a priori default model when the input-yield relationships lack explanatory power within some climate bins for some crops.

The parameters $b_K$, $Y_{maxRF}$, $c_N$, $c_P$, and $c_K$ are defined by the nonlinear regression. We allow $b_K$ to float in order to reflect the higher soil availability of potash relative to nitrogen and phosphorus. The parameter describing the rainfed maximum yield ($Y_{maxRF}$) is not fixed, since this value is climate-specific. Nitrogen, phosphate, and potash response coefficients ($c_N$, $c_P$, and $c_K$) are constrained to be within 5x of the global response coefficient for a particular crop.

When inclusion of a particular input in the combined equation doesn’t contribute to minimizing error in the residuals, that input is removed as an explanatory variable and we do not calculate a bin-specific response to that input. For example, although there may be a small amount of irrigation within a high-precipitation bin, irrigation may not influence yields within this climate and thus we throw out $Y_{maxRF}$ as an explanatory variable (in this case yields are modeled solely as a function of nutrients as in Eqn. 2-S2).
Model evaluation

Sensitivity to soil quality and slope

Soil quality and slope can impact yields at the field scale (Lal 2006). While currently available global soils data has many limitations (Batjes 2006, Sanchez et al. 2009), we analyzed whether our yield models and yield gap estimates were sensitive to the influence of soil organic carbon (SOC) from the ISRIC-WISE database (Batjes 2006) (aggregated among within-grid-cell soil types according to method C in Batjes et al. (Batjes 2006)) and the workability soil quality indicator (as a proxy for soil texture) from the FAO-IIASA Harmonized World Soil Database (Nachtergaele et al. 2012). Workability categories are defined as 1) no or slight constraints, 2) moderate constraints, 3) severe constraints, 4) very severe constraints, 5) mainly non-soil, and 6) permafrost area. We also examined sensitivity to slope constraints as quantified by FAO-IIASA (van Velthuizen et al. 2007). Slope categories are defined as 1) no constraints, 2) very few constraints, 3) few constraints, 4) partly with constraints, 5) frequent severe constraints, and 6) very frequent severe constraints, and 7) unsuitable for agriculture.

We first examined raw correlation between climate-normalized global yield gaps and the additional variables (e.g. Figure 2-S2abc). SOC displayed surprisingly little correlation to percent of attainable yield achieved. R-squared statistics for the correlations were $\leq 0.01$ for all crops except for the weak positive correlations of oil palm, maize, and soybean ($r^2 = 0.04$, 0.02, and 0.03, respectively). Workability correlations were generally weak and directionally inconsistent, with the strongest relationships for soybean (a negative relationship with $r^2 = 0.08$) and sugarbeet (a positive relationship with $r^2 = 0.06$). Slope correlations were generally stronger than the other variables examined, although they remained
directionally inconsistent between crops. Maize and soybean had the strongest negative relationships ($r^2 = 0.13$ and 0.09, respectively) between percent of attainable yield achieved and slope, while oil palm had the strongest positive association ($r^2 = 0.07$).

The yield gap correlations above may be misleading when SOC, workability, or slope are also correlated with management practices. Thus, we constructed added variable plots (e.g. Figure 2-S2def) to assess the unique explanatory power of the additional variables when controlling for both climate and management. Each additional variable was regressed onto the modeled yields, and the residuals from these regressions were used as explanatory variables to explain the residuals from the yield model described by Eqns. 2-S2 and 2-S6. The added variable plots show little unique yield variability explained by SOC, workability, and slope. No r-squared statistics > 0.01 were observed for the SOC added variable plots. All added variable plots for workability showed r-squared statistics ≤ 0.02, with the exception of the negative relationship for sunflower ($r^2 = 0.03$). All added variable plots for slope showed r-squared statistics ≤ 0.02, with the exception of the negative relationships for barley, sunflower, maize, and soybean ($r^2 = 0.03$, 0.03, 0.05, and 0.04, respectively). Added variable plot results suggest that slope may be the most important of the additional variables considered, and we highlight slope as a potentially important topic for future work. However, given the inconsistency in the impact (and direction) of slope on yield for different crops, as well as its relatively weak explanatory power when accounting for management practices, we chose not to incorporate slope into our analysis.

Given the agronomic knowledge about the importance of SOC, workability, and slope at the field scale, it is surprising we did not see greater sensitivity to these
variables. One possible reason for lack of sensitivity is the quality of the global soils data, which is known to need improvement (Batjes 2006, Sanchez et al. 2009). Another possible explanation is the landscape scale of this analysis. Variability of growing conditions can impact yields within a single field, and the aggregation that occurs with landscape-level yield and soil/slope statistics may remove much of the yield signal. Moreover, farm management practices also heavily influence soil characteristics, and this variability is not captured in the global soils data. An updated soils dataset utilizing the state-of-the-art data (Sanchez et al. 2009) could enable better quantification of the role of soils in determining both observed and attainable yields.

**Cross-validation**

Model prediction error was assessed using 5-fold cross-validation. For maize, wheat, and rice, we divided unique census-unit yield observations within each climate bin into five 20% (by area) samples. For each sample, yields were predicted using model coefficients calibrated using the four other samples. This technique allows us to test how well the model performs on independent validation samples.

Cross-validation modeled yields (predicted yields for all five samples using the cross-validation technique) were compared with full-sample modeled yields (model output generated when all the data is used to calibrate the coefficients). Across all three crops, cross-validation modeled yields had ~0.1 t/ha higher root mean squared error (RMSE) than the full-sample modeled yields (full-sample modeled yield RMSE was 1.38, 0.83, 0.94 t/ha for maize, wheat, and rice, respectively, compared to cross-validation modeled yield RMSE of 1.47, 0.91, and 1.05 t/ha). Cross-validation modeled yield r-squared statistics were 0.76,
0.68, and 0.68 for maize, wheat, and rice, respectively, compared to full-sample modeled yield r-squared statistics of 0.79, 0.74, and 0.74. These results suggest that the modeling approach is robust and is not overly dependent upon the data utilized to calibrate the model.

**Analyzing yield-limiting factors and input tradeoffs**

Utilizing the crop- and climate-specific input-yield models, we are able to assess input requirements for achieving a given yield. We apply these tools to assess input requirements for current yields (to determine possible decreases in input use) and input requirements for various scenarios of closing yield gaps (to determine possible increases in input use).

**Assessing possible input reductions**

Possible input reductions are calculated by estimating necessary input application given yield limitation by other inputs. First, yields are modeled using the suite of input-yield models for maize, wheat, and rice. For each crop, we then assessed the nitrogen, phosphate, potash, and irrigation levels necessary to achieve current modeled yields. On each grid cell, one of the aforementioned inputs will be limiting, and the others will be more or less in balance with that limiting nutrient. We calculate “required” nutrients as the amount of other inputs needed when all inputs are in balance. This approach explicitly examines nutrient imbalances, but implicitly also examines inefficiencies in use of particular inputs. For example, we may quantify possible nitrogen reductions in a given area; this overuse of nitrogen may be a function of imbalanced nutrient supply and/or a function of widespread inefficiencies in nitrogen application and uptake.
To assess input increases to close yield gaps, we first identify grid cells where we quantify yield gaps at a given level (i.e. 50% of attainable yields or 75% of attainable yields) using our empirical crop yield data. In climate bins where we do not have an irrigation response parameterized (i.e. including a value for $Y_{maxRF}$ did not aid in minimizing regression residuals), we can simply assess input requirements to close yield gaps using Eqn. S3. In climate bins with an irrigation response, closing yield gaps may be achieved through a combination of nutrient and irrigation changes to the cropland within these grid cells (e.g. Figure 2-S5). We explicitly explore the complexities of this multidimensional yield response surface by considering only changes to nutrient application (1), only changes to irrigated area (2), or joint changes to nutrient application and irrigated area (3).

1. To assess whether yield gaps could be closed with nutrient-only intervention, we first fixed irrigation levels to those observed in the MIRCA2000 dataset. We then calculated areas where yield gaps could be closed with increasing nutrients utilizing the models of yield response to nutrients given a certain level of irrigation (Eqns. S3-S6). Given the asymptotic nature of the yield response to nutrients, some grid cells are modeled as able to close the yield gap but utilize unrealistic nutrient application rates. To account for this issue, we calculate the 95th percentile of globally observed N, P$_2$O$_5$, and K$_2$O application rates for the crop of interest. We only categorize grid cells as able to close yield gaps with nutrients only when projected nutrient requirements are within these 95th percentile application rate limits.
2. To assess whether solely increasing irrigated area could close yield gaps, we again utilize our models of yield response to nutrients and irrigation (Eqns. 2-S3 and 2-S6). Fixing nutrient application, we solve for the irrigation levels needed to close yield gaps. Grid cells are classified as able to close yield gaps with irrigation only when irrigated proportion needed to achieve the desired yield level is ≤1.

3. To project input changes under joint irrigation and nutrient intervention, we calculate the nitrogen by irrigated area (NxI) response surface for each climate bin as in Figure 2-S5. Given limitation by other inputs, we first determine the “effective” nitrogen fertilization rate. Using the effective nitrogen fertilization rate and the current irrigated area proportion, we determine the current placement of the grid cell on the NxI yield response surface. We calculate the contour on the NxI surface corresponding to our desired yield level (50% or 75% of attainable yields) and normalize the nitrogen axis to a 0-1 scale using the 95th percentile of crop-specific nitrogen application. We then determine the minimum-distance change in nitrogen and irrigation to meet this contour. Phosphate and potash requirements for the desired yield are then calculated with the new irrigated area proportion.

For the above analyses, a special case arose when we lacked a climate bin-specific response for a particular nutrient input. Such a situation arises when the inclusion of that nutrient in the combined model did not contribute to minimizing error in the residuals, and thus was dropped as an explanatory variable. In these cases, we estimate the input-yield curve using the bin-specific yield maximum ($Y_{\text{max}}$) and the average response coefficient of interest ($c_N$, $c_P$, or $c_K$) across all the bins in which we had parameterized that response coefficient. Likewise, the
y-intercept for the potash curve (defined by $b_K$ as the proportion of $Y_{max}$ achievable with no additional potash inputs) is estimated using the average $b_K$ across all bins where the response is parameterized.

**Yield-limiting factors**

We categorically assess yield-limiting factors (Figures 2-3, 2-S3, and 2-S4) by comparing current input use against projected required inputs needed to close yield gaps (when both nutrients and irrigated area are allowed to change). Grid cells are categorized having achieved the target yield when either the observed yields (Monfreda et al. 2008) or the modeled yields exceed the target yield.
Supplementary Information – Discussion

Comparison to previous yield gap analyses

Climate bins used in this analysis are defined by empirical growing degree-day and annual precipitation data. Previous yield gap analyses used a modeled water stress or aridity index (actual / potential evapotranspiration) as a moisture variable (Licker et al. 2010, Johnston et al. 2011). To remove model dependence, we examined several crop-relevant empirical moisture variables in preliminary analyses: an empirical aridity index (precipitation / Thornthwaite potential evapotranspiration), annual precipitation, or precipitation during the growing season. The different moisture variables had little effect on the magnitude or spatial patterns of yield gaps. Given the lack of sensitivity, we chose to utilize annual precipitation in our analysis in order to utilize the simplest possible metric.

In addition, we utilized a climate contour technique to identify climate outliers, equal-area binning, and a more restrictive definition of similar climates than climate bins used in previous analyses (Licker et al. 2010, Johnston et al. 2011). These methodological details prevent us from attempting to calculate AYs in anomalous climates and ensure an adequate sample size of grid cells within each climate bin. The more restrictive definition of similar climate generally results in slightly more conservative estimates of potential production, but allows us to capture a greater amount of yield variation due to climate for many crops (Table 2-S3).
Limitations of the analyses

The fertilizer dataset, yield gap estimates, and yield models presented here are not without limitations, which we discuss below.

Our crop-specific, sub-national fertilizer application rates provide a more detailed and comprehensive picture of global nutrient use than previously assembled data (Potter et al. 2010, Liu et al. 2010, MacDonald et al. 2011a), yet we still encountered considerable data limitations in many lower- and middle-income countries. Furthermore, data from multiple sources did not always reconcile and we were forced to make a number of judgments on how best to integrate the data sources. In some case, our ability to reconcile the different datasets differed by nutrient, with more anomalies arising for phosphate and potash than nitrogen. For example, in the US, our initial estimates of nitrogen consumption (using the crop-specific application rates) aligned quite well with FAO nitrogen consumption, and we only needed to scale application rates for “untrusted” crops. For phosphate and potash in the US, our consumption estimates from the crop-specific data did not closely align with the FAO consumption data and we were forced to scale all the crop application rates downward a considerable amount. Improved underlying data is needed to reconcile these disagreements.

Attainable yield and yield gap estimates are quantified using census-derived observed yield data from Monfreda et al. (Monfreda et al. 2008), and AYs are identified from locations elsewhere on the globe with similar annual climate characteristics. As such, AYs are conservative estimates of landscape-scale achievable yields circa the year 2000 and not estimates of physiologically achievable potential yields (for a thorough discussion of yield potential quantification, see Lobell et al.) (Lobell et al. 2009). However, as noted in the
main text, our AY calculations are likely more realistic than biophysical potential yields for defining intensification potential on regional and global scales. Yet a drawback of this technique is that we may underestimate AYs if no high-performing regions fall within a climate analog. For example, in certain climates we may not observe any truly high-performing areas, and thus we may be underestimating yields attainable under more intensive management regimes (e.g. we observe relatively small yield gaps in the Sahel for sorghum and millet due to a lack of high-performing grid cells elsewhere within those climate bins, although we speculate that it is unlikely these areas have truly small yield gaps). Yield gap and attainable yield quantification could be improved in further studies by attempting to include the effects of intra- and inter-annual climate variability. We also note that observed yields can be affected by farmer choice in multi-cropping systems. Further efforts should be made to analyze the magnitude of this effect on AY and yield gap calculations.

The yield models developed in this study describe observed patterns of agricultural productivity (Monfreda et al. 2008) for most major crops (Table 2-S1), but are dependent upon input data of varying quality and scale. The models usefully characterize global patterns of input-use efficiency, but obscure fine-scale details about input-yield relationships and impacts of precision techniques. Yield models generally perform well for input-dependent crops grown in areas where data is likely more reliable, but do not perform as well for some tropical crops due to factors including a lack of high-performing climate analogs, poor data quality, or missing information about important management practices for these crops. Despite these limitations, we believe conclusions from the models can diagnose broad-scale trends across landscapes and regions. Moreover, the models provide a useful framework for further large-scale, quantitative analysis of agricultural management and crop production.
We lacked data to assess management practices other than fertilizers and irrigation in the analysis, although many of these practices may positively co-vary with our explanatory variables. Among the important practices to consider as high-quality data becomes available are the following: crop-specific manure application rates (particularly important in tropical settings) (Smil 2000, Potter et al. 2010), distribution of advanced seed, drainage and water management, plant population, prevalence of agro-ecological techniques for improving soil health and nutrient recycling, common crop rotations and impacts on growing season length, advanced precision management techniques, and crop protection through chemical or agro-ecological means. Estimates of yield-limiting factors, nutrient imbalances, and inputs to close yield gaps could change as additional management practices, particularly organic nutrient inputs, are considered.

This analysis uses a cross-sectional approach with spatial data circa the year 2000 to assess opportunities for intensification, but detailed analysis of temporal yield, attainable yield, and harvest efficiency data are also needed to understand intensification pathways. Beyond yields, the harvest efficiency of cropland has changed over time (FAOSTAT 2012); additional work must assess the opportunities and environmental tradeoffs for increasing cropping intensity and decreasing pre- and post-harvest crop losses.
Figure 2-S1. Global a) nitrogen, b) phosphate, and c) potash consumption from fertilizer application as mapped using our crop-specific and, where available, sub-national dataset.
Figure 2-S2. Wheat sensitivity analysis for (a,d) soil organic carbon, (b,e) soil workability category, and (c,f) slope category. Plots (a,b,c) show the raw correlation between yield gap (defined as the percent of attainable yield achieved) and the additional variables, while the added variable plots (d,e,f) show variation explained by these variables when controlling for management and climate. For (b,c), width of the boxplot is proportional to the area contained within each category, illustrating that most wheat area is grown in areas without substantial workability or slope constraints.
**Figure 2-S3.** Management factors limiting yield gap closure to 75% of attainable yields for **a)** barley, **b)** sugar beet, and **c)** oil palm. Median management models for these crops had the largest explanatory power (Table 2-S1) across our 17 crops.
Figure 2-S4. Management factors limiting yield gap closure to 50% of attainable yields for a) maize, b) wheat, and c) rice.
Figure 2-S5. Example modeled yield surface response to increasing irrigated area proportion in a grid cell and nitrogen fertilizer application rate (kg/ha). Response is shown for maize climate bin 32 (GDD base 8°C = 1974 to 2321, precipitation = 573 to 648 mm/yr).
Figure 2-S6. Model results indicate decreases in a) nitrogen and b) phosphate application rates are possible without affecting yields for maize, wheat, and rice.
Figure 2-S7. Projected changes in a) phosphate application rates and b) potash application rates necessary to close maize, wheat, and rice yield gaps to 75% of attainable yields, and c,d) projected net changes when eliminating input imbalances and inefficiencies.
**Figure 2-S8.** Crop-specific climate bin maps for a) maize, b) wheat, and c) rice.
<table>
<thead>
<tr>
<th>crop</th>
<th>median within-bin rmse (t/ha)</th>
<th>median within-bin $r^2$</th>
<th>global rmse (t/ha)</th>
<th>global $r^2$</th>
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<td>0.68</td>
<td>8.05</td>
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**Table 2-S1.** Root mean squared error (RMSE) and $r$-squared statistics for the median (defined by $r$-squared) within-climate bin management model and the combined suite of 100 climate bin-specific models. R-squared statistics for within-bin models measure within-bin yield variance explained by the management model, whereas the global $r$-squared statistics measure the global yield variance explained by the suite of models.
<table>
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<th>data type</th>
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<tr>
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<td>Brazil</td>
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<td>national-level application rates by crop</td>
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<td>UNIFA</td>
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<td>2005-2006</td>
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<td>India</td>
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<td>Italy</td>
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<td>2002</td>
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<td>FAO</td>
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<td>USDA ERS</td>
<td>USA</td>
<td>sub-national application rates by crop for select states</td>
<td>1997-2003</td>
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<td>crop</td>
<td>Δ global potential production</td>
<td>$r^2$ - Licker et al. &amp; Johnston et al. climate bins</td>
<td>$r^2$ - Mueller et al. climate bins</td>
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<tr>
<td>----------</td>
<td>-------------------------------</td>
<td>---------------------------------------------------</td>
<td>-----------------------------------</td>
</tr>
<tr>
<td>wheat</td>
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<td>rice</td>
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<td>0.59</td>
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<td>0.56</td>
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<td>0.67</td>
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<td>sugarcane</td>
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<td>0.20</td>
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<tr>
<td>sugar beet</td>
<td>-9%</td>
<td>0.26</td>
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</tr>
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</table>

**Table 2-S3.** Due to methodological differences, estimates of potential production increases are slightly more conservative than those in previous analyses. Differences between the climate bins used in this analysis (“Mueller”) and the climate bins used by Licker et al. (2010) and Johnston et al. (2011) (“Licker”) are analyzed by comparing the differences in global potential production with AYs (using 95th percentile yields within a climate bin, [Mueller potential production - Licker potential production] / Licker potential production) and the amount of global yield variation explained by the climate bins (calculated using an r-squared where the "modeled" yields are the area-weighted average yields within a climate bin). These calculations only include grid cells shared between both analyses, meaning that the grid cells cannot be defined as climate outliers according to the Mueller climate contour method and they must be in a Licker climate bin containing at least five grid cells.
Chapter 3: Exploring global crop yield impacts of changing climate and agricultural management

Continued agricultural intensification and accelerating climate change are two of the most important trends determining the future of global agricultural production (Tilman et al. 2002, Jaggard et al. 2010, Lobell et al. 2011b). Understanding the interplay between these trends is of great importance, particularly the degree to which changes in agricultural management could help overcome projected decreases in crop production from climate change (Easterling et al. 2012). Here we present an exploratory global analysis of how the yields of maize, wheat, rice, and soybean are affected by the combination of climate change and agricultural intensification. For A1B 2050 scenarios of climate change, we find that the production gains from agricultural intensification would be much larger than the projected impacts of the new climate conditions. Under A1B 2050 climate change conditions and no intensification, we project approximately -7, 3, -1, and -3% changes to global maize, wheat, rice, and soybean production, respectively. With intensification of low-yielding areas to 75% of attainable yields (closing yield gaps) we find approximately 20, 35, 17, and 3% overall increases in production. However, the capacity for intensification to overcome climate impacts erodes considerably under uniform global temperature increases of 4-5°C, and we estimate net yield losses for maize, soybean, and rice with a 5°C increase even with yield gap closure to 75% of attainable yields. This analysis demonstrates that joint consideration of climate and agricultural management change is
critically important. Increasing investment in management strategies would reduce the impact of climate change on global agricultural production.

**Main Text**

The intensification of agricultural production during the Green Revolution was a humanitarian success with mixed environmental and social legacies (Tilman et al. 2002, Pingali 2012). Increased production from high-yielding crop varieties, greater use of agricultural inputs, and increased cropping intensity lowered food prices and helped overcome chronic food shortages in many developing nations (Tilman et al. 2002, Pingali 2012). The large increases in productivity on existing croplands are also thought to have avoided substantial land conversion to agriculture, sparing natural ecosystems and mitigating ~2-4 Gt of carbon emissions per year by avoiding extensive land clearing (Burney et al. 2010, Easterling et al. 2012). Yet the intensive nutrient, water, and chemical use that accompanied yield increases also brought widespread environmental degradation, including declining water quality, unsustainable water use, soil degradation, and release of toxic chemicals (Tilman et al. 2002, Foley et al. 2011, Pingali 2012).

Prospects for continued intensification are now more uncertain due to observed trends of yield stagnation (Cassman et al. 2003, Ray et al. 2012, Lin and Huybers 2012), although it is likely that intensification will remain a strong driver of future crop production for years and decades to come (Jaggard et al. 2010). Even without advances in genetic yield ceilings, there still exists potential to close “yield gaps” between yields actually achieved on the landscape and those achievable (with improved agronomic practices) given the biophysical growing conditions (Lobell et al. 2009, Licker et al. 2010, Neumann et al. 2010, Johnston...
et al. 2011, Mueller et al. 2012). Closing yield gaps while still decreasing the
global environmental impact of agriculture may be possible, if more intensive
management practices applied to underachieving areas (Tilman et al. 2011,
Sinclair and Rufty 2012, Mueller et al. 2012) are accompanied by efforts to
restore soil health (Bommarco et al. 2012, Tittonell and Giller 2012), improve
nutrient- and water-use efficiencies (Cassman 1999, Tilman et al. 2002, Foley et
al. 2011, Tilman et al. 2011, Mueller et al. 2012, Brauman et al. 2013), and
increase adoption of agroecological management techniques that provide
multiple ecosystem services (Pretty et al. 2006, Bommarco et al. 2012).

In addition to intensification trends, crop production across the globe is now
increasingly affected by rising temperatures and changing precipitation patterns
(Lobell et al. 2011b). Global temperatures have, on average, increased ~0.13°C
per decade since 1956 and ~0.18°C per decade since 1981 (Solomon et al.
2007). Trends in precipitation are also observed, but are generally weaker
relative to natural variability (Solomon et al. 2007, Lobell et al. 2011b). Changes
in temperature and precipitation impact a suite of important biological processes,
including those that affect photosynthesis and crop development. High
temperatures can elevate evaporative demand and decrease plant water use
efficiency. Heat stress can disrupt key reproductive periods of plant development

While they are both recognized as important forces driving crop production, few
studies have examined the combined impacts of climate change and
intensification on global crop production. While some studies have suggested
that net increases in global crop production are expected to 2050 (through
intensification) despite climate change (Parry et al. 2004, Jaggard et al. 2010),
existing studies often lack geographic detail, crop-specific analysis, and explicit consideration of intensification capacity.

Here we present an exploratory global analysis of how crop production may change under new climate conditions with and without intensification from closing yield gaps. The impacts of climate change on maize, wheat, rice, and soybean yields (baseline circa 2000 areas and yields are shown in Figures 3-S1 and 3-S2) are evaluated for A1B 2050, B1 2050, and uniform global temperature increase scenarios. Yield impacts are estimated using the cross-sectional, fixed-management approach of Gerber et al. (Gerber et al. in prep). This method keeps relative yield attainment (yield gap) constant under climate change, thus simulating a high degree of adaptation. We then examine the intensification potential from closing yield gaps to 75% of attainable yields in the context of new climate conditions, building on previous yield gap assessment techniques (Licker et al. 2010, Johnston et al. 2011, Mueller et al. 2012). We also calculate rainfed attainable yields in order to examine capacity to increase production without expanding irrigation.

We find that the climatic changes expected under 2050 scenarios (Figures 3-S3 and 3-S4) will have substantial and geographically uneven impacts on crop yield over existing crop areas; however, intensification potential from closing yield gaps is substantially larger than the projected climate impact in many regions (Figures 3-1 and 3-2). Under the A1B climate scenario and no intensification, we projected changes of approximately -7, 3, -1, and -3% to global maize, wheat, rice, and soybean production, respectively (uncertainty ranges for all global production results are presented in Table 3-1). But with yield gap closure to 75% of attainable yields under the same climate conditions, we projected net increases of approximately 20, 35, 17, and 3% increases in production.
Figure 3-1: Spatial patterns of yield changes under 2050 climate with and without intensification. Percent change in maize, wheat, rice, and soybean yield, relative to 2000\textsuperscript{33}, for A1B 2050 climate projections with and without yield gaps closed to 75% of attainable yields (YG75). Yield changes by grid cell were averaged across five climate model outputs and eleven climate zone definitions. Results do not include CO\textsubscript{2} fertilization and are calculated over existing crop area\textsuperscript{33}. 
Figure 3-2. Net change in global crop production under climate and intensification scenarios. Percent change in global production with and without intensification for maize, wheat, rice, and soybean under three climate scenarios: T+2°C, A1B 2050, and B1 2050. Error bars show the full range of results across five climate models (for A1B and B1) and eleven climate zone definitions.
and maximum production changes were excluded from the table. Numbers in parentheses are minimum attainable yields. Income level results from the climate scenario combined with intensification to 75% of the intensification scenario across countries of different income levels.

<table>
<thead>
<tr>
<th></th>
<th>A1B</th>
<th>B1</th>
<th>T+2</th>
</tr>
</thead>
<tbody>
<tr>
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<td>CC</td>
<td>CC</td>
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<td>(5.3 -1.3)</td>
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<td>(-5.4 -3.2)</td>
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</table>

**Table 3-1.** Average net yield change by crop, climate scenario, and intensification scenario across countries of different income levels. The “CC” column shows results from the climate scenario alone, while “CC+YG75” shows results from the climate scenario combined with intensification to 75% of attainable yields. Income level-crop combinations with <10 million tons of production were excluded from the table. Numbers in parentheses are minimum and maximum production changes across all GCM and climate zone definitions.
Production increases are projected even when simulating no irrigation expansion (Figure 3-2), highlighting intensification potential on rainfed and existing irrigated areas.

We also investigated how climate change will influence the production capacity of intensification under uniform temperature increase scenarios of 1-5°C (Figure 3-3). We estimated that yield gap closure to 75% of attainable yields combined with a warming of 5°C would result in approximately -2, -4, and -1% declines in maize, rice, and soybean yield, respectively (Figure 3-3). Wheat, which is more routinely grown at high-latitudes (Figure 3-S1), could still experience net yield increases of ~25% under the same scenario (although uncertainty is high, as discussed in SI).

These results suggest that the remaining intensification potential of major crops, using currently available technology and agronomic practices, provides a window of opportunity for increasing production on existing croplands in the face of near-term climate changes expected circa 2050. However, as climate change becomes more extreme – at global temperature increases of ~4-5°C – this window may not persist, and even aggressive intensification through closing yield gaps may not be sufficient to produce net yield increases. In short, the net yield changes across global croplands appear largely driven by intensification for less extreme climate scenarios, but when temperature changes become more extreme, intensification gains are overwhelmed by the impacts of climate change (Figure 3-3).

When only climate change is considered, the Gerber et al. (Gerber et al. in prep) projections show greater proportional yield loss for maize under A1B, B1, and T+2°C scenarios in low-income countries. These results are consistent with previous studies (Parry et al. 2004, Fischer et al. 2005, Nelson et al. 2009),
Figure 3-3. Sensitivity of global crop production and intensification capacity to temperature increases. Percent global production change for uniform global temperature increases of 0-5°C a) without intensification and b) with simulated intensification from closing yield gaps to 75% of attainable yields. Results show that the capacity for intensification to lead to net yield increases erodes with increasing temperatures. Solid lines are averages across eleven climate zone definitions, and shaded area shows the full range of results.
however similar patterns are not found for wheat, rice, and soybean. When we consider both climate change and intensification, we show that the greatest relative potential for intensification from closing yield gaps is located in low- and middle-income countries (Figure 3-1, Table 3-1). Wheat has the largest global intensification potential for yield gap closure under the 2050 climate scenarios, while soybean has the least (Figure 3-2, Table 3-1).

The extent to which yield gaps will actually close across the globe depends on both biophysical capacity and socio-economic capacity. Yield gap analyses highlight regions of the world where agricultural systems ought to be biophysically responsive to changes in management using currently available seeds and agronomic practices. Yet despite biophysical capacity to respond to management changes, yield gaps can persist due to socio-economic constraints such as a lack of capital, inadequate infrastructure, or poor access to functioning markets (Lobell et al. 2009, Easterling 2011, Tittonell and Giller 2012). Our results show that the greatest biophysical capacity to overcome climate-induced yield changes exists in lower- and middle-income countries (Table 3-1), giving hope that it may be possible (with sufficient investment) to offset climate-related losses in places where climate change is expected to hit hardest. However, management changes will only occur if facilitated by transforming socio-economic conditions.

Regions of the world with little to no yield gap and high socio-economic capacity may still be able to achieve future yield growth from advances in crop genetics, precision agriculture, plant protection, and CO₂ fertilization (which will have minimal impacts on C4 crops but will likely increase C3 crop yields by ~13% at 550 ppm CO₂) (Tester and Langridge 2010, Jaggard et al. 2010). Thus, although the capacity of high-income areas to overcome climate impacts by closing yield
gaps may be small, our results are not meant to suggest that yields will necessarily stagnate in these areas. Likewise, our analysis holds crop area fixed, and both high- and low-income areas could also improve overall crop production by altering the mix of crops grown in a given area as their climatic suitability shifts.

The climate analog approach to quantifying yield gaps and attainable yields has been widely used in previous studies (Licker et al. 2010, Johnston et al. 2011, Foley et al. 2011, Mueller et al. 2012), however it is not without limitations. Global-scale methods do not have the same precision as local and regional-scale approaches; for example, they do not consider local crop rotations (van Ittersum et al. 2012) or fine-scale patterns of soil degradation (Tittonell and Giller 2012). However, as the attainable yields used here are derived from high-achieving yields averaged over many farms and reported for census units (and are not derived from computer simulations, test plots, or top-yielding fields), our yield gap estimates should tend to be somewhat conservative. The underlying yield data (Monfreda et al. 2008) sampled to determine attainable yields is a 7-year average; sampling shorter time frames may also overestimate yield gaps (Lobell et al. 2009). A more complete discussion of the yield gap methodology is available in Mueller et al. (2012). We also examined rainfed attainable yields in this study by excluding all political units with 10% or more irrigated area before sampling for the 95th percentile yield. This is a straightforward approach, but comparisons to other approaches are presented in Figure S6.

Uncertainties are also associated with the yield impacts estimated by the cross-sectional method of Gerber et al. (in prep). The methodology tracks changes in attainable yields under climate change, and – by keeping relative yield attainment constant in each location – implicitly simulates high levels of adaptation to
changes in climate. The approach is consistent with our climate analog yield gap methods, allowing for our comparison with intensification. However, the method only simulates changes in mean climate, and not climate variability or extremes. Future climates also present some growing regions with new climatic zones for which we have no current analog, and we are unable to calculated yield changes in these areas (see SI for discussion). The uncertainty analyses presented here allow us to characterize the sensitivity of our results to different input datasets and assumptions, however these results should not be mistaken as representing final confidence intervals. Uncertainties also exist in the underlying crop and climate data.

We also note that previous studies have examined management adaptations to changing climates (Rosenzweig and Parry 1994, Cassman et al. 2011, Easterling 2011, Deryng et al. 2011, Butler and Huybers 2012, Easterling et al. 2012, Gerber et al. in prep), such as changing planting dates (Deryng et al. 2011) and adjusting choice of crop variety or maturity rating (Cassman et al. 2011). There is no clear separation between the management changes that might be labeled “adaptation” and those that might be labeled “intensification”, as some adaptations to new climate conditions may lead to intensification and vice versa. While any distinction is somewhat arbitrary, for the purposes of this study we have conceptualized the difference by defining adaptation as management changes that maintain existing yields relative to their potential (i.e. a constant yield gap), while intensification is a closing of the yield gap or an increase in the yield potential.

In this analysis, we jointly considered climate and management influences on global crop production. We found that closing yield gaps could produce net yield and production gains in many regions, even in the context of climate changes.
expected between now and 2050. However, this capacity for offsetting climate damages through intensification erodes considerably with larger temperature changes, especially those near 4-5°C. Thus, while intensification may be considered a lever to cope with near-term climate change, it does not eliminate the need for aggressive mitigation of greenhouse gas emissions. Our results are consistent with the perspective that management changes can be a powerful lever to adapt to climate change and decrease food insecurity (Brown and Funk 2008, Easterling 2011). Joint consideration of climate change and management influences on global crop yields is a promising area for continued investigation, and is critical for understanding possible futures and leverage points. This topic should be explored using different methodological approaches (including statistical time-series analyses and process-based models) and in the context of different avenues of intensification (e.g. changes to genetic yield potential or improving drought tolerance).

**Methods**

*Climate scenarios*

We utilized a selection of A1B and B1 climate projections for circa 2050 climate (30 year average between 2036 and 2065). Downscaled climate projections from Maurer et al. (2009) were selected for five GCMs: GFDL CM 2.1, ECHAM 5.1, CSIRO 3.0, MRI-CGCM 2.3.2, and CCSM 3. Two of these models (GFDL CM 2.1 and ECHAM 5.1) were selected because they performed well according to metrics established by Gleckler et al. (2008). The other three models were selected to cover the range of temperature and precipitation results (Gerber et al.
in prep). All climate projections from Maurer et al. (2009) were further adjusted by Gerber et al. (in prep) for consistency with the Worldclim climatology (Hijmans et al. 2005) and the 5 arc-minute by 5 arc-minute resolution of the Monfreda et al. (2008) cropland dataset.

Uniform temperature increase scenarios were calculated as simple perturbations of the Worldclim climatology (Hijmans et al. 2005).

Yield impacts of climate scenarios

Crop yield impacts of changing climates were estimated by Gerber et al. (in prep), and here we briefly summarize the method. Zones of similar climates and attainable yields (a conservative estimate of yield potential) were calculated as in Mueller et al. (2012). Within crop-specific, equal-harvested-area climate zones – defined by growing degree days (GDD) and total annual precipitation (TAP) – attainable yields are calculated as the 95th percentile yield (from the Monfreda et al. (2008) circa 2000 crop yield and area dataset) in each zone. For each future climate scenario, we track the new spatial location of these climate zones and the migration of climate-specific attainable yields. Yield impacts are estimated using the ratio of the new attainable yield to the former attainable yield. Thus, a location achieving 80% of the current attainable yield is expected to achieve 80% of the new attainable yield. Changes in production are calculated using circa 2000 crop-specific harvested area data (Monfreda et al. 2008).

Sensitivity to global climate model (GCM) and the number of climate zones was assessed by Gerber et al. (in prep) and continued in this study. Calculations were carried out using climate zones varying from 10x10 (10 zones of GDD and 10 zones of TAP – 100 zones) to 20x20 (400 zones). As detailed by Gerber et al. (in
prep), the number of climate zones has a smaller impact on climate-induced yield change than the choice of GCM.

**Calculating rainfed attainable yields**

Rainfed attainable yields were calculated as the 95th percentile rainfed yield within each climate zone for each crop. Yields from political units with less than 10% irrigated area were considered rainfed. We used the crop-specific, year-long summary maps of the monthly MIRCA2000 irrigation data (Portmann et al. 2010) calculated by Mueller et al. (2012) to define irrigated percentage, and yield data is from Monfreda et al. (2008). Rainfed attainable yields were constrained to be less than or equal to attainable yields. Figure S5 provides an example rainfed attainable yield map for maize.

In a small subset of climate zones for rice and wheat, we lacked sufficient rainfed yield observations in the zone to estimate rainfed attainable yields (using a minimum threshold of three unique yield observations per zone). To be conservative in our estimates of yield changes without irrigation increases, we assumed rainfed attainable yields in these zones were zero. Intensification could still be possible for grid cells located within these climate zones if a proportion of the crop area was irrigated, consistent with the approach described below.

**Estimating yield impacts from closing yield gaps**

We estimated potential crop yield increases from closing yield gaps to 75% of attainable yields (as in Mueller et al. (2012)), accounting for the attainable yield of the new climate zone. Using 75% of attainable yields as the intensification goal is
consistent with previous work (Mueller et al. 2012) and illustrates the importance of considering intensification.

Rainfed attainable yields were used to limit yield increases when considering scenarios to close yield gaps without changing irrigated area. Where irrigated area already existed, we scaled the maximum possible yield based on the current irrigated percentage. For example, the maximum yield that could be achieved on a grid cell with 50% rainfed and 50% irrigated area was the mean of the attainable yield and the rainfed attainable yield.

Calculations of intensification potential in the context of climate change were performed for each combination of GCM and number of climate zones. Yields were only compared in places with yields in both 2000 and 2050 for each scenario, given that some harvested area leaves the “edges” of the GDD x TAP space (for which we have attainable yields parameterized) as the climate zones migrate across the globe (see SI and Gerber et al. (in prep) for more details).
Supplementary Information – Discussion

Novel climates

As noted in the main text, future climates present some growing regions with new climatic zones for which we have no current analog, and we are unable to calculate yield changes in these areas. The crop-specific climate zones used in this study contain ~95% of circa 2000 harvested area for each crop, so areas that are no longer contained within one of the climate zones would likely be experiencing undesirable climates for the crop of interest. As these outlier climates may have relatively low productivity, and they are necessarily excluded from our analysis, this could lead to an under-prediction of negative yield impacts.

New “no-analog” climates occur most dramatically for rice under high uniform temperature scenarios; only ~34% of the rice harvested area originally within one of the climate zones would still experience one of these climates in the T+5°C scenario. It is worth noting that observed warming tends to be concentrated in higher latitudes (Solomon et al. 2007), thus T+5°C over tropical and subtropical rice growing areas would occur under a larger degree of total global surface warming than T+5°C over the relatively higher-latitude wheat areas.

Irrigation

Irrigation will be important for intensification goals in some regions (e.g. Figure 3-S5), however, considerable intensification potential does exist on rainfed and
currently irrigated areas (Figure 3-2). Overall irrigated area is expected to increase in the developing world (Alexandratos and Bruinsma 2012), but increasing irrigation efficiency (Foley et al. 2011, Brauman et al. 2013) and reducing irrigated area in some regions will be needed to cope with growing water scarcity (Tilman et al. 2002).

**Uncertainty in wheat projections**

More of the world’s cropland area is devoted to growing wheat than any other crop, and wheat is widely dispersed across many agro-ecological zones. Global statistics on wheat areas and yields aggregate together a number of different wheat varieties and cropping cycles (i.e. summer and winter wheat). Thus, it is not unexpected that variations in the number of climate zones (used to determine attainable yields), which have relatively small impacts on results for the other crops, result in much larger uncertainty for wheat. How climate change impacts are manifested on a field scale for wheat and all the crops will depend upon the particular crop variety, management practices, and crop calendar adopted by the farmer.
Supplementary Information – Figures

Figure 3-S1. Crop harvested areas circa 2000 (Monfreda et al. 2008) for a) maize, b) wheat, c) rice, and d) soybean.
Figure 3-S2. Crop yields circa 2000 (Monfreda et al. 2008) for a) maize, b) wheat, c) rice, and d) soybean. Yields are displayed across the top 98% of growing area for each crop.
Figure 3-S3. Annual average temperature maps for a) the baseline Worldclim climatology (Hijmans et al. 2005), b) A1B 2036-2065 average (Maurer et al. 2009, Gerber et al. in prep) as projected by GFDL CM 2.1, c) B1 2036-2065 average as projected by GFDL CM 2.1, and d) Worldclim T+2°C. Output from five different GCMs were analyzed for A1B and B1 scenarios.
Figure 3-S4. Precipitation maps for a) the baseline Worldclim climatology (Hijmans et al. 2005), b) A1B 2036-2065 average (Maurer et al. 2009, Gerber et al. in prep) as projected by GFDL CM 2.1, c) B1 2036-2065 average as projected by GFDL CM 2.1. Output from five different GCMs were analyzed for A1B and B1 scenarios.
Maize attainable yields (AYs), rainfed attainable yields, and difference between the two maps. The largest attainable yield differences between irrigated and rainfed maize are in the western US, central Mexico, southern Europe, parts of Sub-Saharan Africa, and eastern China. Attainable yields are calculated as the 95th percentile yield or rainfed yield within a climate zone. Maps displayed here are grid cell means across eleven climate zone definitions.
Figure 3-S6: Rice attainable yields and rainfed attainable yields by climate zone when calculated using alternative methods. The black line shows attainable yields, calculated as the 95th percentile yield within each climate zone. Blue lines show the technique used in this paper for calculating rainfed attainable yields. All political units (from which the yield observations are derived) with greater than 10% irrigated area are excluded from the yield map, then attainable yields are calculated as the 95th percentile of the remaining rainfed yield observations within each climate zone. The green line is calculated similarly to the blue line, except only grid cells with greater than 10% irrigated area are excluded – not the entire political unit. The magenta lines are rainfed yield ceilings derived from the Mueller et al. (Mueller et al. 2012) yield response model. These numbers were calculated using nonlinear regression models relating agricultural inputs to yield in each climate zone, and were only parameterized when they contributed to minimizing model RMSE in a given climate zone.
Chapter 4: Rethinking global cropland nitrogen use tradeoffs

Nitrogen (N) use across global croplands enables high-yielding agricultural landscapes, but does so at considerable environmental cost. Imbalances between N applied and N removed in harvested material leads to excess N in the environment, with negative consequences for water quality, air quality, and climate change. Here we utilize input-yield models to assess how N use could maximize production for three major cereal crops: maize, wheat, and rice. We construct a tradeoff frontier representing the point at which an increase in production necessitates an increase in N use, given that all N is applied to maximize production. We additionally explore potential environmental consequences by calculating excess N along the frontier using a soil surface nutrient balance model. We quantify a considerable opportunity space to achieve greater production and decrease excess N. Current (circa 2000) levels of cereal production could be achieved with ~50% less N application and ~60% less excess N. If current N application were held constant, production could increase ~30%. If current excess N were held constant, production could increase ~40%. Spatial patterns of N use to achieve these gains involve substantial reductions in many high-use areas and moderate increases in many low-use areas. Increases in nitrogen use efficiency would expand the frontier and allow greater production and environmental gains.
Introduction

Improved nitrogen (N) management across global croplands is crucial to maximizing agricultural productivity and decreasing human health and environmental damages (Tilman et al. 2002, Diaz and Rosenberg 2008, Galloway et al. 2008, Foley et al. 2011, Mueller et al. 2012, Sutton et al. 2013). Ammonia synthesis from the Haber-Bosch process allowed a dramatic acceleration of reactive nitrogen (N$_r$) use for agriculture during the latter half of the 20$^{th}$ century. While this technology has enabled large increases in food production, it has also come at substantial costs to ecosystem and human health.

Excess reactive nitrogen (hereafter referred to as excess N) from agricultural systems causes environmental damages in many ecological systems. Excess N in the form of nitrate readily leaches into waterways. Nitrate can contaminate groundwater and contributes to eutrophication of surface waters, decreasing water clarity as well as fish abundance (Tilman et al. 2002, Diaz and Rosenberg 2008, Galloway et al. 2008, Keeler et al. 2012, Sutton et al. 2013). Nitrous oxide (N$_2$O), released from agricultural soils through nitrification and denitrification, is a powerful greenhouse gas that also depletes stratospheric ozone (Davidson et al. 2000, Schlesinger 2009, Pinder et al. 2012, Sutton et al. 2013). Volatilizing ammonia and nitric oxide (NO) emissions from agricultural soils can negatively impact air quality. Excess N can also acidify soil, and atmospheric deposition of N$_r$ can negatively impact terrestrial biodiversity (Sutton et al. 2013). The Haber-Bosch process itself also has substantial environmental impacts; the process consumes ~2% of global energy (Sutton et al. 2013).

Given the non-substitutability of N for plant growth, use of N$_r$ in agriculture cannot simply be replaced or transformed. Instead, the management of global N$_r$
resources – including biologically derived N, – must improve to maximize environmental quality and human welfare.

Imbalances between N applied and N removed in harvested material leads to extreme amounts of excess N in some areas and N deficits in others (Vitousek et al. 2009, Liu et al. 2010, Foley et al. 2011). Efforts to balance patterns of N surplus and deficit could have the additional benefit of improving production outcomes on net, as the yield response to nitrogen is relatively steep at low application rates and shallow to flat at high application rates (Figure 4-1). For example, efforts are being made to cut back on nitrogen overuse in China with no or little impact on crop yields (Ju et al. 2009, Zhang et al. 2013). In the EU, it is estimated that current wheat N application rates are approximately 50 kg/ha higher than what would be socially optimal, given both the costs and the benefits of N application (Davidson et al. 2000, Schlesinger 2009, Pinder et al. 2012, Van Grinsven et al. 2013, Sutton et al. 2013). Elsewhere, cropping systems in some developing countries suffer from too-little N use, which may have detrimental long-term effects on soil quality and yields (Tittonell and Giller 2012, Sutton et al. 2013). In areas of low nutrient application – places at the “steep” end of the N-yield curve – small increases in fertilizer use can help prevent mining of soil nutrients while dramatically increasing yields (Sanchez 2002, Nziguheba et al. 2010, Twomlow et al. 2010, Sutton et al. 2013).

Thus, there are opportunities for more optimal use of agricultural N that would simultaneously increase food production and minimize environmental risk across the globe. Doing so would require reevaluating the geographic intensity of N use, in addition to more efficient timing and placement of application. These opportunities can be mapped using a tradeoff frontier, which is a useful framework for determining potential win-win scenarios between endpoints
Figure 4-1. a) At the field scale, the nitrogen-yield response is generally steep at low application rates and shallow at high application rates, as illustrated by the three tangent lines in this example N-yield response for maize. b) Net excess N release (as calculated from the mass balance model) accelerates at high application rates as less of the additional N is removed in the harvested material. The yield response function used here is characteristic of maize in north-central Iowa, USA circa 2000, and we assume an additional 30 kg/ha of N deposition and N manure inputs.
seemingly in conflict (e.g. Polasky et al. 2005, 2008). The frontier tracks the point at which an increase in production necessitates an increase in N use at current efficiency levels, given that all N is applied to maximize production.

In this analysis, we construct a tradeoff frontier for global nitrogen use and cereal production. We model how nitrogen could be utilized to maximize production for three major cereal crops: maize, wheat, and rice. We assume other nutrients are not limiting, and nitrogen use efficiencies (crop production realized for a given application rate) follow the nitrogen use efficiency (NUE) levels circa 2000 implicit in a suite of crop- and climate-specific N-yield curves (Mueller et al. 2012). We additionally explore potential environmental consequences by calculating excess N using a soil surface nutrient balance model for each point along the frontier.

**Methods**

**Building the N consumption-production tradeoff frontier**

Mueller et al. (2012) estimated Mitscherlich-Baule (M-B) nitrogen-yield curves and rainfed maximum yields for crop-specific climate zones (100 zones per crop). These curves were parameterized by utilizing global data on crop yields (Monfreda et al. 2008), fertilizer application (Mueller et al. 2012), irrigated area (Portmann et al. 2010), and climate (Hijmans et al. 2005). Additional bootstrap analysis (with 999 repetitions per climate zone per crop) provides a 95% CI on the M-B response coefficients. For some crop-climate zone combinations, adding N into the regression did not minimize root-mean square error of the model fit (if more variability was explained by irrigation and the other fertilizer nutrients). In
these cases, we utilize average response coefficients across all climates (and upper and lower bound response coefficients from the bootstrapping results) in conjunction with climate-specific minimum and maximum yields to estimate an expected N-yield response.

Using the crop- and climate-specific N response curves, we build a tradeoff frontier relating total global production to total global N use. For increasing amounts of total nitrogen consumption, we assume fertilizer N is applied geographically (between climate zones) to maximize production, with dY/dN equal on every curve (for 30 dY/dN values from 2 to 0.0001). This exercise results in a series of crop-specific production and nutrient application maps for every point on the tradeoff frontier, which are then summed across the globe to determine total global production and nutrient consumption per crop. Similar calculations are made for a scenario with no changes to irrigated areas, where N application rate increases stop on rainfed areas when yields reach the rainfed yield ceilings of Mueller et al. (2012).

To aggregate tradeoff frontiers across multiple crops, we keep the observed proportion of N allocation between crops (circa 2000) fixed, and then add up production at different levels of total N use. Spline interpolation in MATLAB R2012b was used to interpolate between points on the crop-specific curves. Finally, we overlay 1997-2003 N consumption by crop (Mueller et al. 2012) and 1997-2003 cereal production (Monfreda et al. 2008) to assess the current N use and production situation relative to the frontier. All calculations are performed over the 95% of crop area encompassed by the crop-specific climate zones.

Soil surface nutrient balances
Nitrogen balance calculations are carried out using the approach of Foley et al. (2011), building on earlier nutrient balance work for both nitrogen (Bouwman et al. 2005, Liu et al. 2010) and phosphorus (MacDonald et al. 2011b). This method tracks all of the N inputs (fertilizer, manure, atmospheric deposition, and legume fixation) and outputs (removal of N in harvested material) spatially for each 5 arc-minute by 5 arc-minute grid cell across the globe. We modify the approach of Foley et al. (2011) to assess crop-specific N balances by distributing manure N between the top 20 crops within each grid cell, in proportion to the harvested area of each crop. Legume fixation rates are not included, as we only examine cereal crops in this study.

As we build the nutrient consumption and production frontier (Figure 4-2a, 4-S1a, 4-S2a, 4-S3a), we generate a new fertilizer application rate map and a new yield map for each crop at each point on the curve. These maps are used as inputs to the N balance model to generate a map of excess N at every point, which is summed up to create the excess N and production tradeoff frontier (Figure 4-2b, 4-S1b, 4-S2b, 4-S3b).

Results

Across major cereals, we find that the distribution of N application and production (circa 2000) is situated considerably within the tradeoff frontier for production and both N use and excess (Figure 4-2). Specifically, we find that production could be held constant and nitrogen use could drop approximately 48% (lower and upper-bound results with 95% CI on N response coefficient: 37-55%). Alternatively, N use could be held constant and global production of major cereals could increase approximately 28% (20-34%) via changes in the geographic intensity of N use.
Figure 4-2. Global-scale tradeoff frontiers for a) major cereal production and N consumption and b) major cereal production and excess N as defined by a soil surface nutrient balance model. Shaded areas represent uncertainty ranges calculated with a 95% CI on the N response coefficients.
Assuming no changes in irrigated area resulted in a relatively small drop in production potential at high N consumption values (Figure 4-2).

With the N excess-production tradeoff frontier, we find that production could be held constant and N excess could decrease approximately 61% (49-67%). Nitrogen excess could be held constant and production could increase approximately 39% (29-46%).

Spatial patterns of N application intensity change under optimized scenarios (Figure 4-3). For example, when total N use is held constant but is applied to optimize modeled production, large decreases in N use are seen across China, the United States, India, and parts of Western Europe. In contrast, much of Eastern Europe, Africa, and Latin America show increases in N application rates.

Maize, wheat, and rice cultivation are responsible for relatively similar amounts of global excess N circa 2000. Across the top 95% of crop area modeled in this study, we calculate maize N inputs to be 12.0 Mt N in chemical fertilizer, 4.0 Mt N in manure, 0.6 Mt N from atmospheric deposition. Excess N of maize is approximately 8.6 Mt, or 51% of all maize N inputs. We find wheat N inputs of 14.7, 4.6, and 0.8 Mt N from chemical fertilizer, manure, and atmospheric deposition, respectively. Excess N of wheat is approximately 10.4 Mt, or 52% of total wheat N inputs. We find rice N inputs of 12.8, 5.4, and 0.6 Mt N from chemical fertilizer, manure, and atmospheric deposition, respectively. Rice had the largest amount of excess N of the three crops: 12.0 Mt N, or 64% of all rice N inputs.
Figure 4-3. Changes to N application rates under a production-optimized scenario with constant N application and no changes to irrigated area. a) Average N application rates for maize, wheat, and rice circa 2000. b) Optimal nitrogen application rates for major cereals, with constant total global N consumption. c) Difference between current application rates and the optimized scenario.
Discussion

**Increasing production and decreasing excess N**

The tradeoff frontier for N use and cereal production potential quantifies the large potential for changes to global N management that both decreases excess N and increases crop production. This analysis illustrates how increasing food production globally does not necessarily need to come with increased excess N in the environment. Pathways to achieve this change involve a reallocation of geographic N use intensity: decreases in areas where current N use is high, and increases in areas where N use is currently very low. In addition, the whole system could and should improve by increasing the overall efficiency of N use (see section: *Moving the tradeoff frontier*), as the models we use to construct the tradeoff frontier are calibrated to circa 2000 efficiency levels.

The frontier determines a range of potential options to improve the N-production tradeoff, and it is not a prescription for any particular management change. However, analyzing spatial patterns from an “optimized” scenario relative to the current situation (Figure 4-3) provides insight into the direction and magnitude of changes possible to both application rates and production.

Moving towards more “optimal” patterns of N intensity would likely require substantial changes to infrastructure and markets. For example, regions in sub-Saharan Africa with low nutrient use suffer from extremely high fertilizer prices due to overland transport costs. In addition, markets not equipped to handle crop production surpluses can lead to price crashes which disincentivize management for higher productivity (Sanchez and Swaminathan 2005). Likewise, incentivizing
lower use in areas of currently high use may be politically challenging unless reductions can be done in a way that doesn’t hurt farm profits and productivity.

Impacts on human well-being

Reallocating N intensity to both increase production and decrease excess N would likely benefit human well-being in diverse ways. In many regards, increasing production in currently underachieving areas would promote food security where it is currently needed most. However, while food availability is necessary to ensure access to healthy, safe, and nutritious food (Barrett 2010), it is not sufficient to ensure food security. Poverty, markets, infrastructure, and institutions also play a major role (Food and Agriculture Organization of the United Nations 2012).

Decreasing excess N in the environment would benefit human well-being through several different pathways. Human health would improve by decreasing nitrate-contaminated water and improving air quality (Keeler et al. 2012, Van Grinsven et al. 2013, Sutton et al. 2013). Recreation value of aquatic ecosystems would increase from improvements in water quality (Keeler et al. 2012). Fishing and food provision would benefit from improved water quality and climate change mitigation (Keeler et al. 2012, Easterling et al. 2012). Biodiversity, which is appreciated for its intrinsic value and importance in underpinning myriad ecosystem services, could benefit from improved air and water quality, less severe climate change, and reductions in N, deposition (Keeler et al. 2012, Sutton et al. 2013).

Efforts to reallocate fertilizer application intensity would decrease N₂O emissions disproportionately to any reduction in N fertilizer use, leading to compounding
benefits for climate and stratospheric ozone. This is due to nonlinear increases in N₂O emissions at high N application rates, particularly when there are large imbalances between applied and removed N (Van Groenigen et al. 2010, Philibert et al. 2012).

Future research should attempt to systematically quantify the social costs and benefits of agricultural N across the globe (e.g. Van Grinsven et al. 2013, Sutton et al. 2013). Combined with information on private economic returns to agricultural N use, such information would allow greater insight into N management scenarios that maximize social benefits.

**Moving the tradeoff frontier**

The present analysis and proposed tradeoff frontier should be viewed as a first estimate and a snapshot in time, characterizing the production possibilities and tradeoffs with circa 2000 technology and average efficiencies. Substantial changes to the frontier are possible with improved practices and technologies (Figure 4-2), thus the current estimate is somewhat conservative.

A variety of management techniques could increase on-field NUE and decrease excess N. Such strategies are generally characterized under the “4R Nutrient Stewardship” paradigm, which promotes use of the right fertilizer source with the right application rate, timing of application, and fertilizer placement in order to increase nutrient use efficiency (IFA Task Force on Fertilizer Best Management Practices 2009, Robertson et al. 2012). Integrated management systems that incorporate these factors have provided dramatic experimental evidence that NUE boundaries can be aggressively pushed to increase productivity and decreasing excess N (Zhang et al. 2011, 2013). For example, Chen et al. (2011)
were able to double maize yields in China while completely eliminating excess N by applying N in 5 split doses with soil testing guiding application rates. Increasing adoption of these sophisticated agronomic practices could dramatically push the tradeoff frontier as illustrated in Figure 2. However, despite this large potential for improving NUE, observed NUE trends are relatively flat across both developed and developing countries (Conant et al. 2013).

Increasing biologically-derived N inputs can decrease dependency on chemical N for fertility, although may not necessarily lead to decreases in excess N (Cassman et al. 2003). However, organic inputs are especially critical for replenishing soil carbon (Sanchez 2010) and ensuring responsive soils (Tittonell and Giller 2012). Agroforestry with leguminous trees, mixed cropping systems, and appropriate crop rotations can replenish soil fertility (Sanchez and Swaminathan 2005).

Other agronomic improvements, such as appropriate plant population, protection from pests and diseases, and improved seed can also improve field-scale NUE (Cassman et al. 2003). In addition, landscape management with perennial vegetation can capture runoff and winter cover crops can reduce N\textsubscript{r} losses (Robertson et al. 2012).

Future work should quantify how adoption of practices that improve NUE would change the tradeoff frontier and the current N-production status (i.e. changes to Figure 4-2). Such efforts would require consistent assessments of how global fertilizer use is allocated between different crops over time.

**Uncertainties and limitations**
The nitrogen-yield response curves utilized in this study represent a general yield response for a given range of growing conditions and are not appropriate for quantifying yield response for specific fields under specific management regimes. The curves are calibrated to average NUE circa 2000, and not theoretically optimal NUE (e.g. Carberry et al. 2013). Given the scale at which the curves were parameterized, the curves do not capture variability in NUE and yield that can occur at fine spatial and temporal scales in response to field-specific management and soil conditions (Cassman et al. 1996, 2002). Likewise, this model only captures yield as a function of applied N, not plant-available soil N, so it does not simulate indigenous N supply or how that stock may change between years or with specific cropping systems or soil conditions.

The bootstrapping analysis undertaken here does not present a formal confidence interval on the tradeoff frontier, as we only present a bootstrapped CI on the M-B response coefficients. Yield y-intercepts and asymptotes are set using the 2nd and 98th percentile yields per climate bin. If high-yielding areas were not observed within a climate bin, the asymptote for the yield response could be artificially low. In some climate bins, N-specific curves were not parameterized as they didn’t lead to a reduction in regression RMSE when including data on irrigation, phosphorus, and potash application. In these cases the analysis relies upon average response coefficients for the crop.

The soil surface nutrient balance model used utilizes detailed spatial data on nutrient inputs and outputs to estimate excess N. Our approach is based entirely upon earlier work (Liu et al. 2010, MacDonald et al. 2011b, Foley et al. 2011), except that we generate crop-specific nutrient balances by apportioning manure inputs between crops proportionally to the area in each crop. The manure data is likely the most uncertain aspect of the spatial N balance approach, given the
relatively rough estimates about the proportion of manure generated that is applied (see Liu et al. 2010, MacDonald et al. 2011b, Foley et al. 2011). Given the lower confidence in the manure application data, we choose to leave manure out of the yield response model, but include it in the N balance model. This allows us to roughly include the influence of manure in determining excess N without introducing data artifacts into the yield model.

Conclusions

This analysis quantifies the substantial improvements possible in crop production and reduction of both applied and excess N. Our results suggest global benefit from reductions in N intensity in some regions and increases in N intensity in others, along with wholesale increases in NUE across the entire system. Such changes would be critical steps towards meeting the projected increases in food demand (Tilman et al. 2011) while improving environmental quality. We suggest that the methodology adopted here – a crop production and environmental outcome tradeoff frontier – be utilized more widely to help determine production possibilities in agricultural systems that maximize human well-being. These analyses could and should be carried out at many different scales and over time, with the potential to improve land-use decision-making.
Supplementary Information – Figures

Figure 4-S1. Maize tradeoff frontiers for a) applied and b) excess nitrogen.
Figure 4-S2. Wheat tradeoff frontiers for a) applied and b) excess nitrogen.
Figure 4-S3. Rice tradeoff frontiers for a) applied and b) excess nitrogen.
Chapter 5: Conclusion

A note to academic readers: this conclusion was written in the hope of eventually adapting the text for a popular audience.

In the coming years, we are faced with the daunting task of producing nearly twice as much food while attempting to stabilize our climate and improve the ecological health of our lands and waters. Agricultural intensification, the process by which farmers and ranchers are able to produce more food on the same amount of land (e.g. a greater yield), is often seen as a solution to this challenge. Such optimism is partly based on history; between 1985 and 2005, we were able to increase crop production 28% while only increase the cropland footprint by 2.4% (Foley et al. 2011). However, there is mounting concern about whether such gains can continue indefinitely (Cassman et al. 2003, Ray et al. 2012)

While avoiding agricultural expansion is beneficial to biodiversity and the climate (keeping carbon on the land, not in the air), the yield increases we have seen over the past decades were made possible through intensive management of nutrients, water, pests, and diseases. Given that these practices often have clear downsides for the environment, intensification seems to represent something of a Faustian bargain. We might get more food with less land, but we also get water scarcity, nutrient pollution, greenhouse gas emissions, and release of toxic chemicals.

Throughout this dissertation, I’ve asked two main questions about the future of agricultural intensification. First, is there potential for continued intensification of the world’s crops? And second, what are the tradeoffs to intensification, and can
they improve? More specifically, is there potential that intensification could be done in a way that improves food production, environmental quality, and human well-being?

The work presented here has shown that considerable intensification potential still exists on the world’s croplands, even with current levels of technology. Specifically, improving management on the least productive lands represents a major opportunity. Closing the “yield gap” between these areas and the top performers with similar growing conditions could boost production ~45-70% for many crops.

Our projections estimate that closing a portion of the yield gap (to 75% of attainable yields, a ~30% increase in major cereal production) would require fairly substantial increases in nutrient use across some regions of the globe. Nitrogen application in Eastern Europe would need to look a lot more like nitrogen application in Western Europe. In Africa, where hardly any chemical fertilizers are used, a small increase would be needed. Irrigation may need to change as well. Our projections suggest it would be difficult to close yield gaps in Northeast Brazil, East Africa, parts of India, and Northeast China without increases in irrigated area. While the UN’s Food and Agriculture Organization still projects some increases in irrigated area (Alexandratos and Bruinsma 2012), many accessible water supplies have already been exploited for irrigation. Moreover, irrigation is expensive and faces strong competition from other water users. However, despite these challenges, considerable intensification potential does exist.

Climate change poses an additional threat to agriculture, and there is widespread concern that climate change could imperil food security. However, few global-
scale assessments have truly considered how climate change and intensification may proceed in tandem. We analyzed this critical issue and found that intensification through yield gap closure has the potential to overcome climate change impacts in 2050 across much of the world. However, we also found that climate changes of 4-5°C erode the potential of yield gap closure to produce net yield increases. Thus, intensification provides us with a window of opportunity to manage our greenhouse gas emissions – not an indefinite solution. If we don’t get our emissions under control, our food supply could be in serious long-term trouble.

These research endeavors show the incredible importance of intensification to our food supply, but a central challenge remains: how can we “do” intensification better? Nitrogen use presents an interesting case study for analyzing production possibilities. Greater nitrogen use is associated with higher yields, but the yield effect saturates at high application rates, leaving more and more of the applied nitrogen “left over” as excess. These releases of excess nitrogen end up in our waters and in the atmosphere, damaging human health and a diverse array of important ecosystem services. Given these relationships, it is hardly ideal to have some agricultural regions with incredibly high nitrogen use (and thus high excess nitrogen) and some regions with incredibly low nitrogen use (and thus low production).

We constructed a tradeoff frontier for more optimal nitrogen use on cereal crops. The frontier shows the point at which an increase in production necessarily requires an increase in nitrogen use, given that all the nitrogen is applied “optimally” to maximize production. We found that our current situation is very far from the frontier. For example, current production could be achieved with half the nitrogen currently used. Making this change would actually decrease the excess
nitrogen released to the environment by around 60%. Moreover, there are plenty of opportunities to increase production and decrease nitrogen pollution, even with current levels of efficiency in agricultural systems. Innovative work that improves nitrogen use efficiency could improve the production potential even more. Our study isn’t a prescription for a particular change to nitrogen management, but rather points the way towards many better outcomes for food production and the environment.

I have been fortunate to study such an interesting topic for my dissertation, and I hope that the analyses presented here are useful to scientists, policymakers, and practitioners working to improve the food system. Working at the global scale has been especially fulfilling. Even though agricultural management is inherently local, our food system challenges are more global and interconnected than ever before. Taking a global perspective in these analyses helped us understand differences between regions and analyze the promise of potential solutions. We must build on the knowledge presented here and in other studies, integrating knowledge across scales in order to meet the many challenges facing the food system.
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