



Yield gap analysis with local to global relevance—A review

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ABSTRACT

Yields of crops must increase substantially over the coming decades to keep pace with global food demand driven by population and income growth. Ultimately global food production capacity will be limited by the amount of land and water resources available and suitable for crop production, and by biophysical limits on crop growth. Quantifying food production capacity on every hectare of current farmland in a consistent and transparent manner is needed to inform decisions on policy, research, development and investment that aim to affect future crop yield and land use, and to inform on-ground action by local farmers through their knowledge networks. Crop production capacity can be evaluated by estimating potential yield and water-limited yield levels as benchmarks for crop production under, respectively, irrigated and rainfed conditions. The differences between these theoretical yield levels and actual farmers' yields define the yield gaps, and precise spatially explicit knowledge about these yield gaps is essential to guide sustainable intensification of agriculture. This paper reviews methods to estimate yield gaps, with a focus on the local-to-global relevance of outcomes. Empirical methods estimate yield potential from 90 to 95th percentiles of farmers' yields, maximum yields from experiment stations, growers' yield contests or boundary functions; these are compared with crop simulation of potential or water-limited yields. Comparisons utilize detailed data sets from western Kenya, Nebraska (USA) and Victoria (Australia). We then review global studies, often performed by non-agricultural scientists, aimed at yield and sometimes yield gap assessment and compare several studies in terms of outcomes for regions in Nebraska, Kenya and The Netherlands. Based on our review we recommend key components for a yield gap assessment that can be applied at local to global scales. Given lack of data for some regions, the protocol recommends use of a tiered approach with preferred use of crop growth simulation models applied to relatively homogenous climate zones for which measured weather data are available. Within such zones simulations are performed for the dominant soils and cropping systems considering current spatial distribution of crops. Need for accurate agronomic and current yield data together with calibrated and validated crop models and upscaling methods is emphasized. The bottom-up application of this global protocol allows verification of estimated yield gaps with on-farm data and experiments.

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1. Introduction

Whereas seven years ago there was relatively little concern for meeting projected food demand through improvements in crop productivity, today there is increasing awareness that “business as usual” will not allow food production to keep pace with demand—a situation that may result in dramatic rises in food prices, poverty, and hunger (FAO, 2003, 2006; Royal Society of London, 2009; Koning and van Ittersum, 2009; Godfray et al., 2010). Indeed, until recently, the most widely used computational equilibrium

models that evaluate global food supply and demand predicted that grain prices would remain constant or decrease in coming decades (Rosegrant et al., 1995, 2002; Colby et al., 1997; Cranfield et al., 1998; Rosegrant and Cline, 2003).

Three things are responsible for this remarkable turnaround in prognosis for global food security: (1) economic development rates in the world's most populous countries have consistently exceeded projections by a wide margin; (2) large increases in demand for energy, grain, and livestock products in these countries due to a rapid rise in purchasing power; and (3) global slowing of crop yield rates of grain (Cassman et al., 2003, 2010; Steinfeld et al., 2006; Royal Society of London, 2009; Brisson et al., 2010; Fischer and Edmeades, 2010). It is now clear that during the next several decades, as human population rises towards a climax at 9 + billion,

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every hectare of existing crop land will need to produce yields that are substantially greater than current yield levels. However, some regions have much greater potential than others to support higher yields in a sustainable manner, due to their favourable climate, soil quality, and in some cases, access to irrigation. In some of these favourable regions current average farm yields are low. Hence, a large exploitable gap exists between current yields and what is theoretically achievable under ideal management.

Given the need for sustainable intensification, identifying regions with greatest potential to increase food supply is critical for four reasons. First, yield gap analysis provides the foundation for identifying the most important crop, and soil and management factors limiting current farm yields and improved practices to close the gap. Second, to enable effective prioritization of research, development, and interventions. Third is to evaluate impact of climate change and other future scenarios that influence land and natural resource use. And fourth, results from such analysis are key inputs to economic models that assess food security and land use at different spatial scales. Computable general and partial equilibrium models typically rely on historical yield trends with some kind of extrapolation into the future. However, the agronomic basis of such projections and associated resource requirements can be much improved through rigorous yield gap analyses.

For all these reasons, a geospatially explicit assessment of exploitable gaps is required for the major food crops worldwide with local, agronomic relevance and with public access. And while more detailed information about yield gaps is necessary, it is not sufficient to fully inform research prioritization and investment strategies. Analyses of markets, policies, infrastructure and institutional factors are also needed. Without yield gap assessment coupled with appropriate socio-economic analysis of constraints to improved productivity, policy makers and researchers will find it difficult to accurately assess future food security and land use change. This in turn may lead to policy development and research prioritization that are not well-informed, especially in developing regions such as Sub-Saharan Africa and South Asia where current information is sparse.

The usefulness and rigor of yield gap analyses is demonstrated by various examples. Already in the 1960s, when average farmer yields were below 5 Mg ha^{-1} in the Netherlands, it was computed that wheat yields could exceed 10 Mg ha^{-1} (De Wit, 1959; Alberda, 1962). While few believed this could be true at that time, since 1993 average farmers' yields in important wheat growing areas in the Netherlands have regularly exceeded 9 or even 10 Mg ha^{-1} (Centraal Bureau voor de Statistiek). In Australia, the early work of French and Schultz (1984) estimated water-limited yields and showed that yields were limited by factors other than water, despite farmers' perception that water was the single most limiting factor. Recognition of these other limiting factors led to identification of improved management practices such that yield gaps are now smaller (Hochman et al., 2012a,b). Yield gap analyses for Southeast Asia helped explain yield trends in irrigated rice and revealed that nitrogen management had to be improved to increase yields (Kropff et al., 1993). In Nebraska, recent yield gap analysis of irrigated maize identified the recent plateauing of yields in farmers' fields to be associated with a yield level about 85% of the yield potential ceiling (Grassini et al., 2011a), which is similar to yield levels at which other crops have plateaued (Cassman et al., 2003, 2010).

This review aims at comparing and assessing different methods of yield gap analysis across spatial scales from the field, to sub-national and national scales, to identify key components of yield gap analysis that ensure adequate transparency, accuracy, and reproducibility. In this paper we begin with definitions and a conceptual framework for agronomically relevant yield gap assessment, and then evaluate the strengths and limitations of previously

published local and global yield gaps. Based on this analysis, we identify the key components and associated uncertainties of a global protocol for yield gap analysis to produce locally relevant outcomes that can be aggregated to regional or national estimates.

2. Concepts

Yield potential (Y_p), also called potential yield, is the yield of a crop cultivar when grown with water and nutrients non-limiting and biotic stress effectively controlled (Evans, 1993; Van Ittersum and Rabbinge, 1997). When grown under conditions that can achieve Y_p , crop growth rate is determined only by solar radiation, temperature, atmospheric CO_2 and genetic traits that govern length of growing period (called cultivar or hybrid maturity) and light interception by the crop canopy (e.g., canopy architecture). Potential yield is location specific because of the climate, but in theory not dependent on soil properties assuming that the required water and nutrients can be added through management (which, of course, is not practical or cost-effective in cases where major soil constraints, such as salinity or physical barriers to root proliferation, are difficult to overcome). Thus, in areas without major soil constraints, Y_p is the most relevant benchmark for irrigated systems or systems in humid climates with adequate water supply to avoid water deficits. For rainfed crops, water-limited yield (Y_w), equivalent to water-limited potential yield, is the most relevant benchmark. For partially (supplementary) irrigated crops, both Y_p and Y_w may serve as useful benchmark. Definition of Y_w is similar to Y_p , but crop growth is also limited by water supply, and hence influenced by soil type (water holding capacity and rooting depth) and field topography (runoff).

Both Y_p and Y_w are calculated for optimum or recommended sowing dates, planting density and cultivar (which determines growing period to maturity). Sowing dates and cultivar maturity are specified to fit within the dominant cropping system because the cropping system "context" is critically important in dictating feasible growth duration, particularly in tropical and semi-tropical environments where two or even three crops are produced each year on the same piece of land. Farmers attempt to maximize production and/or profit for the entire cropping system rather than the yield or profit of an individual crop. Likewise, where machinery and labour are limiting or costly, achieving optimal sowing dates may not be feasible for most farms. We therefore argue it is also relevant to calculate Y_p and Y_w for current average or median planting dates in addition to optimal dates.

Average yield (Y_a) is defined as the yield actually achieved in a farmer's field. To represent variation in time and space in a defined geographical region, it is defined as the average yield (in space and time) achieved by farmers in the region under the most widely used management practices (sowing date, cultivar maturity, and plant density, nutrient management and crop protection). The number of years utilized for estimating Y_a must be a compromise between variability in yields and the necessity to avoid confounding effects of temporal yield trends due to technological or climate change (see Section 4).

The yield gap (Y_g) is the difference between Y_p (irrigated crops), or Y_w (rainfed crops) and actual yields (Y_a). Water resources to support rainfed and irrigated agriculture also are under pressure, making water productivity (WP—the efficiency with which water is converted to food) another critical benchmark of food production and resource use efficiency (Bessembinder et al., 2005; Passioura, 2006; Grassini et al., 2011b). Water productivity is defined as the ratio between (grain) yield and seasonal water supply, which includes plant-available soil water at planting, in-season rainfall, and applied irrigation (irrigated crops) minus the residual plant-available water in the root zone at maturity.

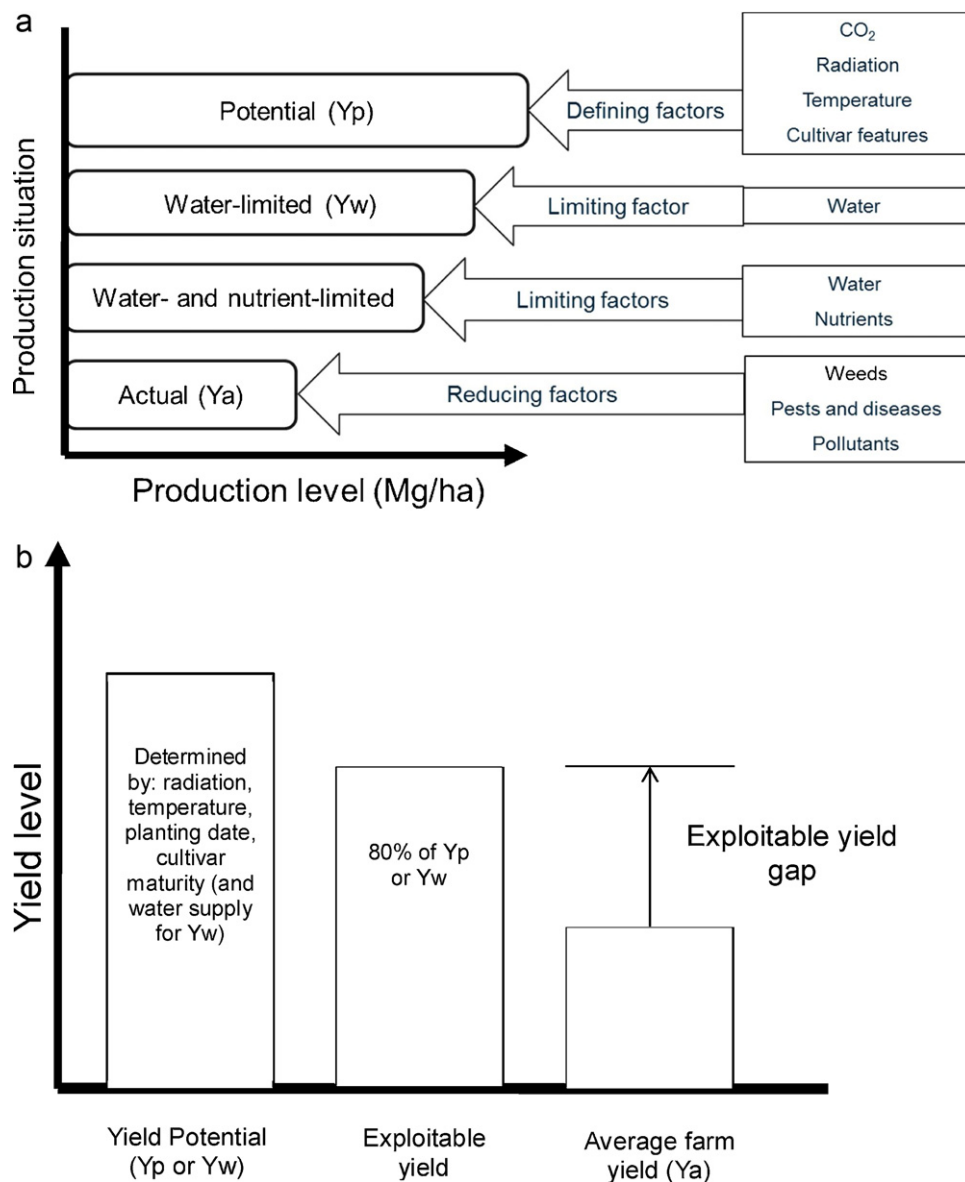


Fig. 1. Different production levels as determined by growth defining, limiting and reducing factors (a). Yield potential (Y_p) of irrigated crops without limitations due to water deficiency or surplus is determined by solar radiation (R), temperature regime (T), and growth duration from planting to maturity. For crops grown under rainfed conditions, the water-limited yield (Y_w) represents the ceiling yield (Van Ittersum and Rabbinge, 1997). The exploitable yield gap (b) represents the difference between average yields and 80% of Y_p or Y_w , as explained in the text (modified from Lobell et al., 2009).

Both Y_p and Y_w are defined by crop species, cultivar, climate, soil type (Y_w), and water supply (Y_w), and thus both Y_p and Y_w are highly variable across and within regions. However, it is impossible for a large population of farmers to achieve the perfection in crop and soil management required to achieve Y_p or Y_w , and generally it is not cost-effective to do so because yield response to applied inputs follows diminishing returns when farm yields approach ceiling yields (Koning et al., 2008; Lobell et al., 2009). Also, there may be valid reasons from a resource use efficiency point of view (De Wit, 1992) to aim for closing yield gaps at a lower yield level threshold relative to Y_p or Y_w under conditions with greater uncertainty in factors governing these ceiling yields—such as high temperatures, variable rainfall, high winds that promote lodging, and so forth. Because average farm yields tend to plateau when they reach 75–85% of Y_p or Y_w , the exploitable yield gap is smaller than Y_g (Van Ittersum and Rabbinge, 1997; Cassman, 1999; Cassman et al., 2003). Taken together, Y_p , Y_w , Y_g , and WP determine crop production potential of current cropping systems with available land

and water resources. A schematic representation of these critical parameters is presented in Fig. 1.

We note, that Y_p , Y_w , Y_a and Y_g must be estimated for a defined geographical unit and time frame. They can be quantified for individual farmers' fields for a given year, or for larger areas and longer time periods, by accounting for their spatial and temporal variation using appropriate upscaling procedures (Ewert et al., 2011). And while climate change may alter Y_p , Y_w , Y_a , and Y_g , through direct changes in temperature and water availability or farmers' adaptations in terms of planting dates and cultivar maturities, and also (Y_a and Y_g) indirectly through effects on prevalence and severity of pests and diseases, this manuscript focuses on quantifying current values of the various yield levels for two reasons. First, because current values provide the basis for identifying causes of yield constraints and magnitude of potential yield increases. Second, because accurate estimations of today's Y_p and Y_w are essential to benchmark effects of climate change on future yields and food security.

3. Review of methods to assess yield gaps

Yield gaps have been estimated in previous studies with either a global or local focus. Whereas global methods are generally coarse and provide worldwide coverage using a consistent method, local studies are based on location-specific environmental conditions and management, which give local relevance but are hard to compare across locations and studies because of inconsistent terminology, concepts and methods.

3.1. Local studies

At least four methods can be distinguished to estimate yield gaps at a local level (cf. Lobell et al., 2009): (1) field experiments, (2) yield contests, (3) maximum farmer yields based on surveys, and (4) crop model simulations. The first step associated with each method is to estimate yield ceilings as represented by Yp and Yw for a given crop in a given location or region. Yg is then calculated as the difference between farmer's Yp or Yw and Ya.

Although field experiments and yield contests can be used to estimate Yp and Yw for a given location and under a specific set of management practices, they require well-managed field studies in which yield-limiting and yield-reducing factors are eliminated (e.g., nutrient deficiencies, and diseases), and they must be replicated over many years to obtain a robust estimate of average Yp or Yw and their variation (Cassman et al., 2003). The latter may be a serious limitation in practice because it is difficult to avoid all abiotic and biotic stresses and to do so consistently in a field study lasting several years. Also, in real-world farming, single crops are part of cropping and farming systems that often constrain sowing and harvesting dates. Hence, field experiments and yield contests used as a basis for estimating Yp or Yw must use sowing dates and cultivar maturities that are representative of the prevailing cropping systems in the region of interest if they are to serve as benchmarks for these systems.

Surveys among farmers to estimate maximum yields from upper percentiles represent another approach to estimate Yp or Yw (Lobell et al., 2009). If crop production resources (including soil properties) and input levels have also been recorded, methods such as the boundary line approach or frontier analysis can be used to identify the highest yields for a given level of resource availability (Tittonell et al., 2008a; Fermont et al., 2009; Grassini et al., 2009; Hochman et al., 2009; Wairegi et al., 2010; Hochman et al., 2012a). However, if obstacles prevent all surveyed farmers from realizing Yp or Yw, then Yg will be underestimated. Such obstacles must operate at the same scale as the yield gap analysis and could include lack of access to inputs, lack of markets, and lack of knowledge or access to it. While field experiments, yield contests and highest yields obtained by farmers are useful to determine maximum achievable yields in a specific location or across a population of fields (i.e., best genotype \times environment \times management interaction, $G \times E \times M$), it is difficult to know for certain if all biotic and abiotic stresses were avoided. Therefore, yields from these sources may not be adequate to derive robust estimates of Yp or Yw representative of the dominant weather and soil conditions in a given cropping system or region.

To overcome limitations of these approaches, crop simulation models can be used to estimate Yp or Yw (see e.g., Grassini et al., 2011a; Laborte et al., 2012). These simulation models are mathematical representations of our current understanding of biophysical crop processes (phenology, carbon assimilation, assimilate partitioning) and of crop responses to environmental factors (for an overview of many crop growth models see Van Ittersum and Donatelli, 2003). Such models have been designed to account for $G \times E \times M$ interactions. They require site-specific inputs, such as daily weather data, crop management practices (sowing date,

cultivar maturity, plant density), soil properties and specification of initial conditions at sowing, such as soil water availability, and a model configuration that ensures nutrients to be non-limiting. Although specification of weather, soil, and management practices in current cropping systems is essential for robust simulations of Yp and Yw, these data are typically not available for most cropping systems with adequate geospatial detail, even in developed countries. Also, models need to be rigorously evaluated for their ability to reproduce measured yields of field crops that received near-optimal management practices, across a wide a range of environments and management practices. Table 1 summarizes the key attributes of crop growth simulation models that we propose as desirable for use in yield gap assessment.

3.2. Comparison of methods to estimate yield gaps at local level

To assess possible implications of using different methods for yield gap assessment at a local level, we evaluated the following methods on their ability to estimate Yp (or Yw) and Yg across farmer's fields over relatively small geographic areas:

- site-specific simulation of Yp or Yw using crop growth models;
- derivation of Yp or Yw from upper percentiles of farmer's yield distributions;
- maximum yields measured in experimental stations, growers contests, or highest-yielding farmer's fields;
- boundary-function analysis based on the relationship between farmer's yields and water supply.

These comparisons were performed for three cropping systems with varying levels of intensification: rainfed maize in western Kenya, irrigated maize in Nebraska (USA), and rainfed wheat in Victoria (Australia). Underpinning data required to perform these analyses, including simulated Yp or Yw, actual yield and water supply, were retrieved from previously published studies (Tittonell et al., 2008b; Hochman et al., 2009; Grassini et al., 2011a,b). Detailed descriptions of cropping systems, crop models structure and validation, and data inputs can be found in each study. In this example, information about yield, management, weather and soil properties were available for each farmer's field from three years for Nebraska and Victoria and one year for Kenya.

We argue crop simulation modelling is the most reliable way to estimate Yp or Yw and Yg in the context of a specific crop within a defined cropping system because these models can account for interactions among weather, soils and management. Yp, Yw, and Yg estimates based on simulation models are not single values, but rather probability distributions with a mean and range (Fig. 2). Variability in Yw and Yp reflects not only differences in management practices among fields, but also variability in weather and soils across years and fields. Weather variability poses a dilemma for farm managers who face large uncertainty about yield-affecting conditions in the season ahead, which in turn creates uncertainty about the most appropriate level of inputs. If they apply input levels in excess of amounts needed for maximum profit in a year when Yp or Yw is below average due to unfavourable weather, they will likely achieve a small Yg but with smaller profit. On the other hand, if farmers invest too little inputs in a year with high Yp or Yw due to favourable weather, they will miss the possibility of achieving a large profit and will have a large Yg. This is the case for rainfed maize and wheat cropping system examples in Kenya and Australia. However, an important distinction is that, while Australian farmers face greater uncertainty about Yw, they are also much better equipped to cope with this uncertainty, due to better access to information and inputs, than Kenyan farmers who often also face labour constraints because of manual ploughing and

Table 1
Desired attributes of crop simulation models.

Desired attribute	Explanation
Daily step simulation	Simulation of daily crop growth and development based on weather, soil, and crop physiological attributes
Flexibility to simulate management practices	Key management practices include: sowing date, plant density, cultivar maturity
Simulation of fundamental physiological processes	Simulation of key physiological processes such as crop development, net carbon assimilation, biomass partitioning, crop water relations, and grain growth
Crop specificity	Should reflect crop-specific physiological attributes for respiration and photosynthesis, critical stages and growth periods that define vegetative and grain filling periods, and canopy architecture
Minimum requirement of crop 'genetic' coefficients	The model should have a low requirement of crop-site 'genetic' coefficients, preferably only a limited number of phenological coefficients
Validation against data from field crops that approach Yp and Yw	Comparison of model outcomes (grain yield, aboveground dry matter, crop evapotranspiration) against actual measured data from field crops that received management practices conducive to achieve Yp (irrigated) or Yw (rainfed crops)
User friendly	Models embedded in user-friendly interfaces, where required data inputs and outputs can be easily visualized, and with flexibility to modify default values for internal parameters
Full documentation of model parameterization and availability	Publicly available models, published in the peer-review literature, with full documentation and publicly available code, and with reference to data sources for internal parameter values

weeding. As a result, yield gaps are much smaller for rainfed wheat in Australia compared to rainfed maize in Kenya (Yg-to-Ya ratio of 0.4 and 2.2, respectively—Table 2). In the case of irrigated maize in Nebraska, access to irrigation water compensates for weather variability and associated risk, allowing crop producers to optimize their farm management and achieve small Yg (Yg-to-Ya ratio of 0.1).

Empirical methods to estimate Yp, Yw, and Yg are generally based on maximum yields or an upper yield percentile achieved by farmers, and are 'static or non-spatially explicit'. As such they do not reflect the full range of conditions within an agro-ecological zone and cropping system (Fig. 3). The yield achieved by a contest winner or in the highest-yielding fields in any region or season was likely unattainable by most other farmers who did not benefit

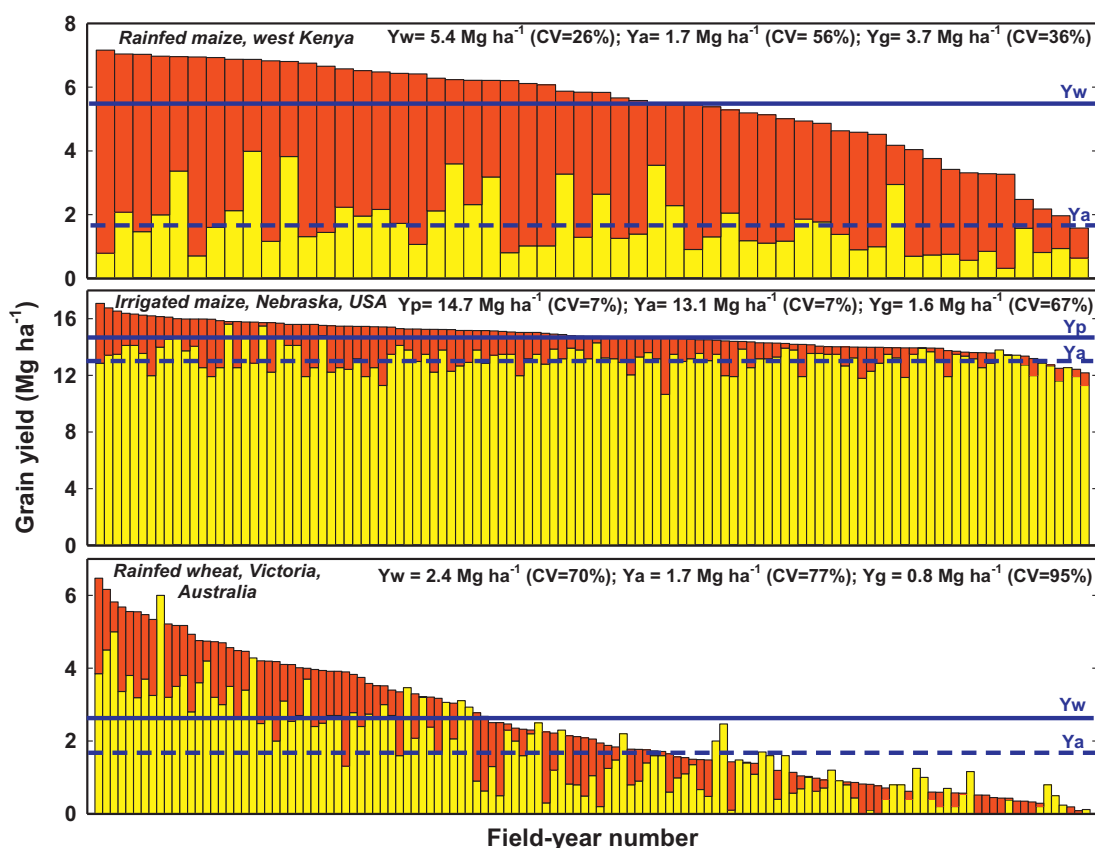


Fig. 2. Simulated yield potential (Yp) or water-limited yield (Yw) based on site-specific weather, soil properties, and management data collected from farmer's fields in three cropping systems: rainfed maize in west Kenya, irrigated maize in Nebraska (USA), and rainfed wheat in Victoria (Australia) ($n = 54, 123,$ and 129 field-year cases, respectively). Each bar corresponds to an individual field-year case. The yellow and red portion of the bars indicate actual farmer's yield (Ya) and yield gap (Yg), respectively. Horizontal lines indicate average Yp (or Yw) and Ya (solid and dashed lines, respectively) for the region. Means and coefficients of variations (CV) for Yp (or Yw) and Yg are shown. Fields were sorted from highest to lowest Yp or Yw. Note, that for the Victoria case, actual yields are higher than simulated Yw for some of the site-years. Explanatory causes include incorrect specification of model inputs (management, soil/weather data), incorrect reported yield, and model error in reproducing some particular $G \times E \times M$.

Table 2

Actual average farmer's yield (Y_a) and estimates of average yield potential (Y_p) or water-limited yield (Y_w), yield gaps (Y_g), and Y_g -to- Y_a ratio ($Y_g:Y_a$) for three cropping systems based on four different methods: crop simulation models, upper percentiles of farmer's Y_a , maximum yields^a, and water-productivity boundary functions (see Figs. 2–4). Values are means for one single year (rainfed maize in western Kenya) or 3 years for irrigated maize in Nebraska and rainfed wheat in Victoria.

Yield (Mg ha^{-1})	Rainfed maize, western Kenya	Irrigated maize, Nebraska, USA	Rainfed wheat, Victoria, Australia
Actual yield (Y_a)	1.7	13.2	1.9
Y_p or Y_w based on:	Y_w	Y_p	Y_w
Simulation model	5.4	14.9	2.6
Upper percentiles Y_a :			
95th percentile	3.6	14.4	3.5
99th percentile	3.9	14.8	4.1
Maximum Y_a^a	6.0	17.6	4.3
Boundary functions	13.0	15.4	3.3
Y_g in Mg ha^{-1} (or as $Y_g:Y_a$ ratio), based on ^b :			
Simulation model	3.7 ($Y_g:Y_a = 2.2$)	1.6 ($Y_g:Y_a = 0.1$)	0.8 ($Y_g:Y_a = 0.4$)
Upper percentiles Y_a :			
95th percentile	1.9 ($Y_g:Y_a = 1.1$)	1.1 ($Y_g:Y_a = 0.1$)	1.9 ($Y_g:Y_a = 1.0$)
99th percentile	2.2 ($Y_g:Y_a = 1.3$)	1.6 ($Y_g:Y_a = 0.1$)	2.2 ($Y_g:Y_a = 1.2$)
Maximum Y_a^a	4.3 ($Y_g:Y_a = 2.5$)	4.5 ($Y_g:Y_a = 0.3$)	2.3 ($Y_g:Y_a = 1.2$)
Boundary functions	11.3 ($Y_g:Y_a = 6.6$)	2.2 ($Y_g:Y_a = 0.2$)	1.4 ($Y_g:Y_a = 0.8$)

^a Maximum yields were derived from measured yields at: nearby experimental stations (rainfed maize in western Kenya), National Corn Growers Association (NCGA) contest-winning irrigated fields in Nebraska (irrigated maize in Nebraska), and highest-yielding farmer field (rainfed wheat in Victoria).

^b For Australia, in few observations, $Y_a > Y_w$; then we assumed $Y_g = 0.0$.

from the same climatic or soil conditions. Likewise, measured yields in experimental stations can also be biased as these stations are often situated on the most fertile soils with favourable topography (i.e., flat land or on well terraced slopes, with deep soil profiles), which can make them poorly representative of surrounding production systems. Hence, maximum yields and upper yield percentiles provide an estimate of the best $G \times E$ interaction across a large population of site-years, rather than a measure of long-term average Y_p or Y_w . Although all these empirical methods are convenient when data are lacking to calibrate and validate a robust crop model and to run it for a range of fields and years, they give inconsistent estimates of Y_p , Y_w , and Y_g compared to those obtained from crop simulation (Table 2). In the case where Y_a is high, which indicates favourable growing conditions and little stress (i.e., irrigated maize in Nebraska) there is relatively close agreement among

Y_p , Y_w , and Y_g estimates based on maximum yields or upper percentiles and estimates based on crop simulation. In contrast, there is very poor agreement among these estimates in cases where farmers do not (or cannot) use best management practices and thus achieve low yields (i.e., Kenya rainfed maize). Likewise, estimates of Y_p or Y_w based on maximum yield or upper percentiles can be heavily biased if there are atypical years or farms amongst the observations, and there is no way of knowing if this is the case without a more detailed analysis using simulation models. This problem plays a role in the dataset for rainfed wheat in Victoria in which the average maximum yield and the average 95 and 99 percentiles of farmer's yields across three years is well above the average simulated water-limited yield over the same period (Fig. 3). If we had taken the maximum yield and 95 and 99 percentiles of farmer's yields while lumping the three years, this difference would be substantially higher as the best year is now used as the benchmark (data not shown).

Boundary functions based on the relationship between actual yields and water supply (or another limiting factor) can be considered as a reasonable approach to estimate Y_p and Y_g when crop simulation models and required data inputs are not available (Fig. 4). Major limitation in using boundary functions arises from not accounting for factors that cause variation in Y_w at the same level of water supply such as distribution of rainfall relative to crop growth stage, and variation in solar radiation and temperature. However, a major strength of this approach is that estimates of Y_w are not “static or non-spatially explicit” values like those derived from upper yield percentiles or maximum yields. Instead, boundary functions provide estimates of Y_w across a wide range of water supply, and Y_g can be estimated for any field-year observation as the difference between actual farmer's yield and Y_w derived from the boundary function at the same level of water supply. Furthermore, use of a boundary function may help to determine the presence of limiting factors other than water supply (French and Schultz, 1984; Grassini et al., 2009; Hochman et al., 2009). For example, Fig. 4 contrasts irrigated maize in Nebraska (rarely water-limited and close to Y_p) with rainfed wheat in Australia (mostly water-limited and close to the boundary) on one hand, versus, rainfed maize in Kenya (presumably less water-limited but still far from the boundary) on the other. According to the boundary function water-limited maize yields in western Kenya and Nebraska are comparable (13.0 and 15.4 Mg ha^{-1} , respectively), but average Y_a of rainfed maize in Kenya is 87% lower than irrigated maize yield in Nebraska due to

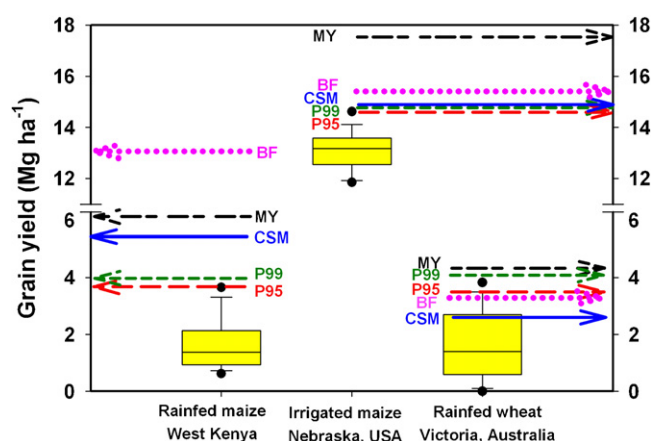


Fig. 3. Box plots showing distribution of actual farmer's yields in three cropping systems (box indicates 25th, 50th, and 75th percentiles; error bars indicate 10th and 90th percentiles; solid circles indicate 5th and 95th percentiles). Arrows show estimates of Y_p (irrigated maize in central USA) or Y_w (rainfed maize in western Kenya and rainfed wheat in Australia) based on different methods: (i) crop simulation models (CSM) based on field-specific actual data on management practices, weather, and soil properties; (ii) 95th and 99th percentiles (P95 and P99, respectively) from the actual-yield distribution; (iii) maximum yields (MY) measured in nearby research station (western Kenya), farmers' contests (USA), or farmer's fields (Australia), and (iv) boundary-functions (BF) for water productivity. Estimations of Y_p or Y_w with the different methods are averages for one single year (rainfed maize in western Kenya) or three years (irrigated maize in USA and rainfed wheat in Australia).

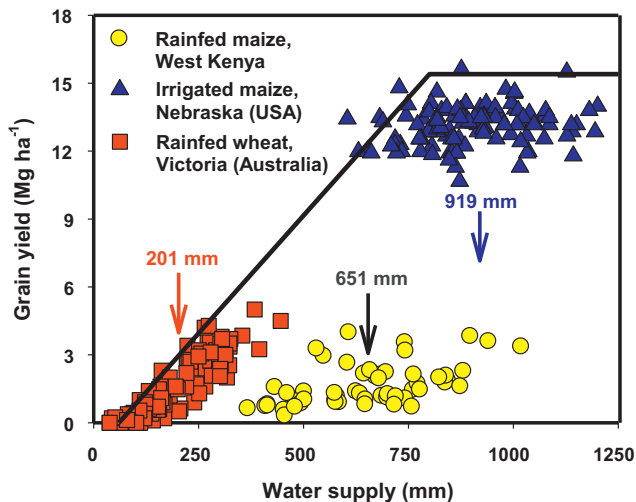


Fig. 4. Actual farmer's yields plotted against water supply. Data were collected from farmers' fields in three cropping systems. Water supply includes plant available soil water at planting plus in-season water inputs from rainfall and irrigation. Estimated surface runoff was subtracted from the estimate of water supply for rainfed maize in Kenya to reflect the actual lower crop water availability due to steep terrain. A boundary function for cereal crops water productivity is shown (solid line), with x-intercept and slope equal to 60 mm and $22 \text{ kg ha}^{-1} \text{ mm}^{-1}$, respectively (Sadras and Angus, 2006) and an upper yield limit of 15.4 Mg ha^{-1} at water supply $\geq 800 \text{ mm}$, established based on highest irrigated maize yields in Nebraska. Average water supply for each cropping system is indicated with arrows. Note, that one boundary function for wheat and maize is assumed. This is justified as there is not too much difference in water use efficiency (WUE) among C3 and C4 crops when comparisons are based on the actual vapour pressure deficits (VPD) of the environments where these crops are typically grown. The difference on WUE between C3 and C4 that would be expected due to the difference in the photosynthetic pathway can only be observed when both types of crops are grown under similar VPD regime, something possible in a greenhouse experiment, but not too common to find in the real world.

rainfall distribution and other limitations such as poor soil fertility, lack of inputs, labour, and knowledge and information about how to deal with these limitations.

3.3. Global studies

Global studies generally use empirical, statistical approaches or generic crop growth models and a grid-based approach using global datasets on climate, soils and sometimes agricultural land use and general crop calendars (Appendix A). The statistical methods take current highest yields within a defined climatic zone (based on e.g., FAO statistics and Monfreda et al., 2008; Licker et al., 2010; Foley et al., 2011; Mueller et al., 2012) or use a stochastic frontier production function (Neumann et al., 2010). They do not verify whether highest yields accurately represent the biophysical Yp or Yw limit as confirmed by either a robust simulation model or field studies. The major limitation of this method is that it does not distinguish between irrigated and rainfed crops; thus, many Yg estimates for a given climatic zone are based on irrigated crop yields—even in regions where the crop in question is grown almost entirely under rainfed conditions. Also, these studies do not explicitly account for differences in crop Yp or Yw within cropping systems that differ in crop rotation or even the number of crops produced each year. Global studies using generic crop growth models utilize a single crop model to simulate generic crop yields for the entire globe. Generally, the papers in which this approach is used do not provide enough information on model calibration and evaluation to determine how robust the estimates are. Often global studies using generic crop growth models do not have the explicit aim to estimate yield gaps; sometimes they aimed at estimating current yields and sensitivities of these yields to variations in management or climate

(Appendix A) (Stehfest et al., 2007; Liu et al., 2007; Deryng et al., 2011).

Studies to estimate Yp, Yw or Ya at global scales using crop simulation models have been based on weather data with sub-optimal temporal or spatial resolution and/or without all necessary weather variables required for accurate simulation of crop performance. For example, most of the studies included in Appendix A used derived climate data interpolated into grids. The interpolation process adds uncertainty into crop simulation for a specific region because the weather data used may not represent the actual weather accurately within the grid. However, a main advantage is that it provides a framework for up-scaling and complete terrestrial coverage. The latter is much more difficult using a point-based approach that requires actual data for weather, soils and crop management. A recent study found that gridded-interpolated weather data give estimates of Yp and Yw that may be considerably different than those obtained from point-based estimates using actual weather data from representative weather stations within the grid (Van Wart, 2011).

Another limitation of published global studies is that estimates of Yp, Yw, and Yg may not represent current management of a cropping system (e.g., crop rotation, planting date, cultivar maturity), which limits agronomic relevance (Appendix A). For example, to estimate Yp and Yw of maize for each major maize-producing country, Nelson et al. (2010) assumed that cultivars had the same maturity in all countries. Actual yields used to estimate Yg are generally based on yields reported in FAOSTAT (FAO, 2012a) and the Agro-MAPS project, a collaboration between FAO, IFPRI (International Food Policy Research Institute), SAGE (Centre for Sustainability and the Global Environment) and CIAT (The International Centre for Tropical Agriculture) (FAO, 2012b). These same actual yield datasets also served as the basis for the crop area distribution maps of Monfreda et al. (2008) that utilized data from subnational levels, where available, and otherwise used national level data from FAOSTAT. Such spatially coarse statistical data on Ya, when combined with more spatially granular weather and soil data, are likely to be an equally important source of error and uncertainty in estimating yield gaps as is uncertainty in the estimation of Yp or Yw.

3.4. Comparing local outcomes of global studies

To assess whether alternative global studies using different methods result in different Yp or Yw and hence yield gaps for specific regions, we asked scientists of published global yield studies to share their data of the grids covering Nebraska (USA), Kenya (maize only) and The Netherlands (wheat only). Table 3 compares data from five studies for which methodological details are provided in Appendix A. This comparison reveals how distinct these studies are in aims, methods and results, whereas at a first glance they may look rather similar. These differences also make comparison of results from such studies difficult and sometimes not justified. Since Stehfest et al. (2007) focused on simulation of nutrient-limited yields as a proxy for actual yields, results of this study for Kenya tell little about Yp or Yw. For Nebraska and The Netherlands, where fertilizer application rates are high, simulated nutrient-limited yields will in theory come close to Yp or Yw. From Deryng et al. (2011) we obtained Yp and Yw for all three countries, but spring wheat was simulated, which is not representative for Nebraska and The Netherlands where winter wheat is grown. Licker et al. (2010) and Neumann et al. (2010) did not discriminate between Yp and Yw—just one value for maximum yield has been estimated. Spatially, Stehfest et al. (2007), Deryng et al. (2011), unpublished results with the LPJmL model (Bondeau et al., 2007; Ch. Müller, Potsdam Institute for Climate Impact Research, Germany) and Licker et al. (2010) did their calculations for all grid

Table 3

A comparison of Yp and Yw (Mg dry matter/ha) of five global yield studies of maize and wheat for Nebraska, Kenya and The Netherlands; Ya based on Monfreda et al. (2008) is provided in the last column. Averages for Kenya and The Netherlands across the grid cells are not weighted for crop area.

Latitude * longitude	Stehfest et al. (2007)		Deryng et al. (2011)		Müller (2012, see Appendix A)		Licker et al. (2010)	Neumann et al. (2010)	Monfreda et al. (2008)
	Yp	Yw	Yp	Yw	Yp	Yw	Yp or Yw	Yp or Yw	Ya
Nebraska-maize									
40.5–41.0°N; 101.5–102.0°W	10.2	3.1	11.6	6.1	8.1	3.3	8.0	9.4	8.5
40.5–41.0°N; 97.0–97.5°W	9.7	5.4	11.3	10.1	8.1	5.9	9.0	9.2	7.9
42.0–42.5°N; 97.0–97.5°W	10.3	5.5	11.6	8.9	7.9	6.7	9.1	8.7	6.4
41.0–41.5°N; 99–99.5°W	9.9	5.2	12.9	9.1	8.1	5.1	9.2	10.1	8.0
41.0–41.5°N; 96.0–96.5°W	9.7	7.7	10.9	10.3	7.9	6.6	9.0	8.4	6.6
40.0–40.5°N; 100.5–101.0°W;	10.1	4.0	11.3	7.2	8.1	3.4	8.0	9.1	7.0
40.0–40.5°N; 99.0–99.5°W	9.8	4.6	11.8	9.3	8.2	4.7	9.2	10.1	8.6
Nebraska-wheat									
40.5–41.0°N; 101.5–102.0°W	4.2	0.9	9.7	6.8	11.2	6.6	3.1	3.5	2.3
40.0–40.5°N; 100.5–101.0°W;	4.1	1.0	9.8	7.8	11.3	7.5	3.1	4.7	2.6
40.0–40.5°N; 99.0–99.5°W	4.2	2.1	10.5	9.1	10.9	8.5	7.2	4.6	2.7
Kenya-maize									
	Na	1.8	9.1	6.3	6.2	3.6	3.4	5.1	1.5
The Netherlands-wheat									
	9.5	9.8	6.2	5.4	8.9	8.3	6.3	Na	7.1

Na: Not available because the crop (irrigated or rainfed) is not very common in that grid or country or no sample grids were available.

cells although size of grid cells differed among the studies, whereas Neumann et al. (2010) took a 10% sample of all cropped 5' × 5' grids to allow for efficient statistical estimations and reduce spatial autocorrelation. Hence for the latter study, averages of the sampled grids were used for the national average, but for some countries (e.g., The Netherlands) no grids were sampled and hence no estimation of the Yp or Yw is available. All these differences between studies motivated a focus on the Nebraska data for a more complete analysis, while for Kenya and The Netherlands (non-weighted) averages per country are provided for the major cropping areas.

For Nebraska, average benchmarks for Yp vary between ca. 8 and almost 12 Mg ha⁻¹ (maize) and ca. 4 up to 11 Mg ha⁻¹ (wheat); effects of water-limitation also strongly differ between the Stehfest et al., Deryng et al. and Müller studies (Table 3). It is not surprising that Licker et al. and Neumann et al. conclude a lower yield potential than studies based on crop simulation models, as the statistical studies base their estimations on actual (average) farmers yields in zones with similar conditions. In low-input crops or climate zones, Yp or Yw will be underestimated by definition. For Kenya, the different studies lead to very different conclusions as to benchmarking irrigated and rainfed maize production. Calculated benchmarks for wheat in The Netherlands also differed substantially between the studies.

As indicated, the studies each had their own aim and methods and differences in estimated Yp or Yw between the five do not tell which study is more valid or accurate; each of them serves its stated purpose at a global level. However, our comparative analysis of local level methods indicates that existing global studies are encumbered with methodological assumptions and large uncertainties in data that prevents them from being a reliable source for location-specific of yield gap estimates. Methodologically, some studies do not allow the determination of yield potential, while all lack the spatial and temporal precision of input data which are required for local accuracy and relevance.

4. Recommendations for a yield gap assessment protocol with local to global relevance

4.1. Need for a bottom up approach to be locally relevant

As demonstrated in Section 3, existing methods lead to different estimates of Yp and Yw, and therefore to differences in conclusions

about magnitude and spatial distribution of Yg. We argue for a transparent, robust and reproducible protocol to estimate yield gaps with local to global relevance. The protocol should be applied consistently across locations and crops in a “bottom-up” approach that optimally exploits local knowledge and data. Global datasets on agricultural management (e.g., Waha et al., 2012) and actual yields (Monfreda et al., 2008) are generally too coarse for local relevance. To allow for regional and global coverage of yield gap assessments there are basically two methods. First, a representative point- or polygon-based approach estimates Yp, Yw, Ya and Yg for selected points or polygons using observed input data and then scales up to higher geographical units. This method assumes that observed or measured weather, soil, yields and cropping systems data are representative for the points or polygons. Second, a grid-based approach (generally used in global studies) uses inter- or extrapolated, gridded, weather, soil and cropping systems data to calculate Yp, Yw (and possibly Ya itself); the outcomes of grids are then upscaled to higher units. We postulate that the first method has the advantage that it is based on local observations and that outcomes of Yp, Yw, Ya and Yg can be verified on-the-ground more readily than for the second method. This allows for a more agronomically relevant estimation of the yield gaps and identification of factors limiting current farm yields. It remains to be investigated which of the two scaling methods (cf. Ewert et al., 2011) leads to the best estimation of yield gaps at larger units, such as provinces, states or nations.

4.2. Estimation of Yp or Yw

Based on Section 3.2 we conclude that simulation models allow for the most reliable estimation of Yp, Yw and Yg because they: (i) account for variation in weather across years and regions, (ii) account for major interactions among crops, weather, soils, water regime and management, and (iii) allow quantification of potential or water-limited productivity within the climatic, soil and management context of a given cropping system. As such, crop models provide the means to capture spatial and temporal variation, to the extent that data are location specific, while this is not possible with any of the empirical methods (record yields, statistical yield distributions or highest yield within a defined agroclimatic or agro-environmental zone).

We propose a number of criteria for selection of an appropriate crop growth simulation model (Table 1). Consistent with a

bottom-up approach, we argue that rather than using a single generic model globally, it is more important that a particular model has been calibrated and evaluated for the conditions to be simulated. Thus, models may differ per location, continent or crop, as long as the models have been validated under those conditions (cf. Fig. 3). Large differences in estimates of Y_p and Y_w from the global studies (Table 3) make it clear that results from generic models need local validation to determine if estimates are accurate. In terms of yield gap analysis, model inter-comparisons, such as in the AgMIP project (Rosenzweig et al., *in press*), can shed light on differences in performance of models for specific locations, if data are available for those locations of studies in which crops are grown under a crop and soil management regime that allows expression of Y_p or Y_w .

4.3. Estimation of Y_a

The accuracy of estimating Y_g is determined by the weakest link, which perhaps in many cases may be the actual yields (Y_a). Accurate geospatial distribution of current crop yields and their spatial-temporal variability are needed, preferably more granular than the FAO data or global datasets based on FAO data (such as Monfreda et al., 2008; You et al., 2009), that use national or sometimes provincial or state-wide averages. More detailed information on actual farmers' yields for specific locations can be based on farmers' surveys and data from wholesale buyers. Some projects are currently underway to achieve this greater spatial granularity, such as Global Futures (<http://globalfuturesproject.com/>) and a number of household panel survey datasets in progress at several international agricultural research centers. Expert knowledge and simple analysis (e.g., relating Y_a to local rainfall) may already help to improve existing aggregated statistics of Y_a at national or sub-national levels.

In favourable, high yield environments, such as for irrigated maize (Nebraska) and rainfed wheat production in The Netherlands, using yields of the 5 most recent years is adequate for estimates of average yield with relatively low coefficient of variation (CV), as 5 years' averages are similar to estimates based on the last 10 years' (Fig. 5). In harsh environments for rainfed crop production, longer time intervals must be considered, and a compromise must be found between adequately capturing variability on the one hand and avoiding the inclusion of technological change (possibly including climate change) on the other hand. So, for Nebraska an average of 10 years is needed, as using fewer years leads to biased estimates of average yield and CV due to the influence of years with exceptionally high or low rainfall during the crop growing season, while longer time intervals include technological change. For the Australian case 15–20 years may be a suitable compromise.

4.4. Data and upscaling

The minimum data to estimate Y_p and Y_w include data on weather (daily time-step T_{max} , T_{min} , precipitation, solar radiation, relative humidity and possibly windspeed), soil (in particular root zone water holding capacity and runoff as determined by soil texture, soil depth and slope) and cropping systems (actual and optimal sowing and harvesting dates, cultivar maturity, and optimum plant population density). We propose to use local agronomic information obtained from literature, surveys, government agencies, international institutions, or experts. Increasingly global databases with sowing and harvesting dates are becoming available (e.g., Bondeau et al., 2007; Waha et al., 2012), and these can eventually be used as a substitute, but only if local, observed data are not available.

We also argue for use of daily observations of the weather; various authors have demonstrated that interpolated monthly observations may lead to overestimations of simulated yields in particular in locations with high day-to-day variability in weather conditions (Nonhebel, 1994; Soltani et al., 2004; Van Bussel et al., 2011). Weather data should be quality controlled and preferably have a time series of >15 years (Van Wart et al., 2013a). If measured solar radiation is not available (which is often the case) then these can be based on data from the NASA agroclimatology solar radiation data (Bai et al., 2010; Van Wart et al., 2013b). If time series of >15 years observed weather data are not available, such series could be generated from shorter periods of observed data with additional calibration sources, or if no observed data are available, gridded, generated weather data may need to be used.

Assuming the choice for a point or polygon-based approach and observed data (as opposed to generated or interpolated data), we recommend use of spatial maps of crop areas (e.g., the MIRCA dataset of Portmann et al., 2010, the SPAM dataset of You et al., 2009 or more refined national maps) as a reference to identify important points or polygons for which Y_g must be estimated for up-scaling to larger geographical units. To account for variation in climate, an agro-climatic zonation (ACZ—Van Wart et al., 2013b) is proposed as the extrapolation domain for upscaling point estimates of Y_p , Y_w , Y_g to regional and national scales. An ACZ is relatively homogeneous in three parameters that are sensitive in defining growth potential for both individual crops and cropping systems: growing degree days, temperature seasonality, and aridity index (Van Wart et al., 2013b). Within an ACZ a limited number of points (defined by their weather data availability) in key cropping areas are used to represent its variation in climate, soils, cropping systems and management (i.e., sowing dates, cultivar maturity, plant population, etc.). Y_p or Y_w are estimated for the dominant soils, cropping systems and management in a defined area (perhaps a circle of 50- or 100-km radius) around the point for which the weather observations are estimated to be representative. Van Wart et al. (2013a) have shown that a fairly robust estimation of Y_p or Y_w at a country level is achieved if ca. 50% of the total harvested area of a crop in that country is covered in this way. This focuses the yield gap assessment on the most important ACZs and specific locations within these ACZs, e.g., those that contain at least a certain percentage of harvested area in a country for a given crop. This is also efficient in terms of additional data collection that can then be focused on these areas.

Regional or national Y_p , Y_w , and Y_g estimates are weighted by production area per ACZ (considering the dominant soil types and cropping systems) rather than an arithmetic average. Measures of spatial and temporal variability must also be considered because both the mean and the variability in Y_p , Y_w , and Y_g are critical for understanding the opportunities to exploit yield gaps.

5. Concluding comments: challenges for the global agronomic community

We have presented definitions and concepts of crop yield gap analysis and compared different methods for a yield gap assessment. This comparison was used as the basis for proposing a set of principles for a yield gap assessment protocol that can be applied across spatial scales and yet produce locally relevant estimations of yield gaps. The protocol, including the effects on Y_g of uncertainties in weather, soil, cropping system management and crop growth simulation models, remain to be tested and refined, a process which is currently undertaken in the Global Yield Gap Atlas project (www.yieldgap.org). Major advantages of the proposed approach are its strong agronomic foundation and the use of a globally consistent procedure that allows validation against

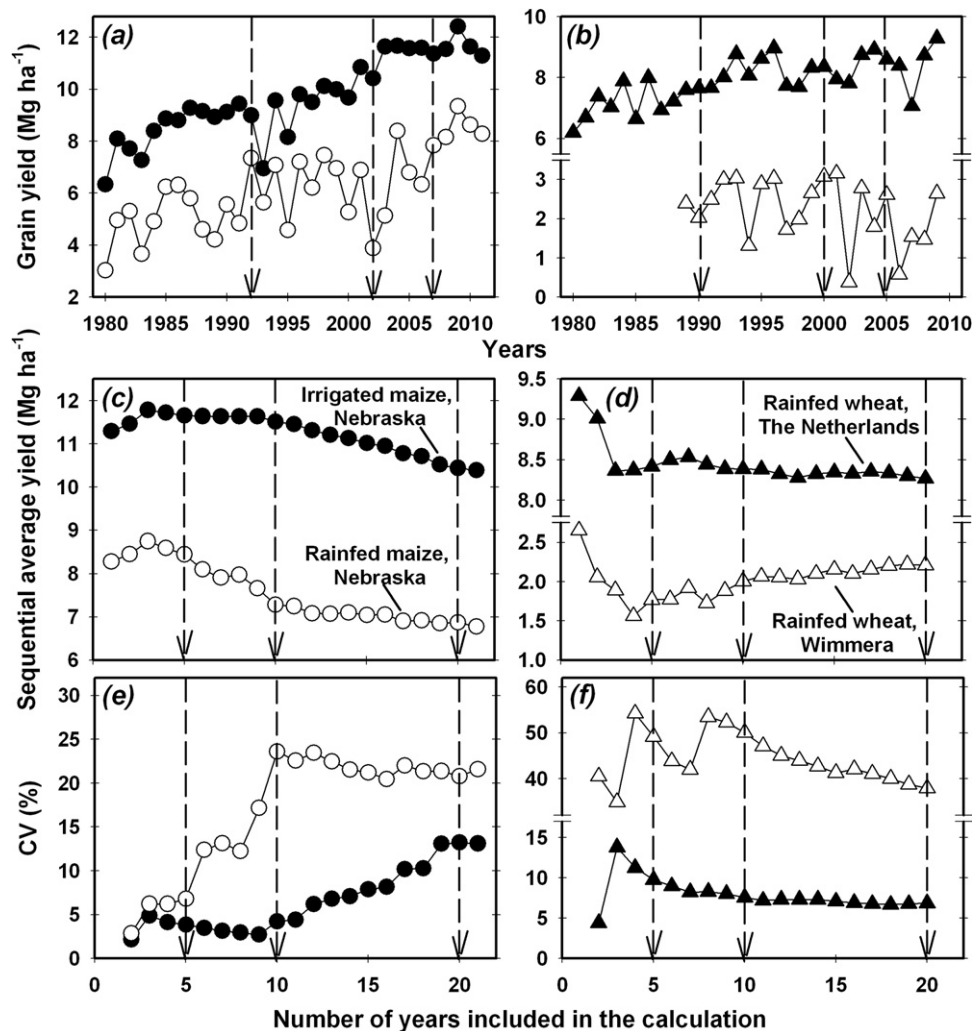


Fig. 5. Trends in grain yields of (a) irrigated and rainfed maize in Nebraska, (b) wheat in The Netherlands and wheat in Wimmera (South-east Australia); sequential average yields starting from the most recent years and gradually including more years back in time (c—Nebraska, d—The Netherlands and Wimmera), and associated coefficients of variation (CV; e—Nebraska, f—Wimmera and The Netherlands) as calculated based on 1, 2, 3... *n* years of yield data starting from the most recent year (2011 for Nebraska and 2009 for The Netherlands and Wimmera) and going backwards. Yields are reported at standard moisture content of 0.155 and 0.145 kg water kg⁻¹ grain for maize and wheat, respectively. The vertical dashed lines indicate the most recent 5, 10 and 20 years included in the calculation of average yields and CVs. Data source: FAOSTAT.

measured yields for Yp, Yw, and Yg. Data availability for weather, soils, crop management and actual yields varies enormously across the globe and will determine whether first or second best options for data sources are used. Crop models are generally available for major crops, such as the primary cereals, soybean and potato, but much less so for other crops including cassava and various pulses. Experiences with yield gap analysis are even more limited with grassland and perennial crops such as oil palm, banana, olive and citrus (e.g., Fairhurst et al., 2010; Wairegi et al., 2010).

As better data become available yield gap assessments can be improved. We therefore strongly argue for a publicly available website with yield gap assessments following a global protocol and making all underpinning data available to users. Likewise, all simulation models that have been used must be available to the public. These standards will provide transparency, reproducibility, and accessibility, and they will allow for continual improvement of the analyses. Open access to underlying data will greatly contribute to efficiency in agricultural research as argued before (White and van Evert, 2008) and it seems timely to join forces with several large international initiatives (Beddington et al., 2012; Rosenzweig et al., in press).

We have shown in this paper there are serious limitations to current estimations of the exploitable gap between current

average yields and yield potential. It is essential that yield gap studies provide clarity regarding their underpinning assumptions, models and parameters and include verification with measured data. Only then can yield gap assessment provide the needed starting point for understanding the scope for increasing human food supply and for (re-) design of systems and interventions to achieve sustainable intensification of agricultural systems around the globe.

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Appendix A. Summary of methods and sources of data in previous global yield studies

Study	Explicit focus on Yp and Yw and source of Ya	Crops	Historical weather data		Soil data	Agronomic data	Crop model
			Source	Time step			
<i>Empirical models</i>							
Licker et al. (2010)	Yp (no explicit difference with Yw)	Maize, wheat, rice, soybean, barley, millet, rye, sorghum, cassava, potato, sugarcane, sugar beet, groundnuts, oilpalm, rapeseed, cotton, pulses, sunflower	Gridded-interpolated (CRU; New et al., 2002; www.badc.nerc.ac.uk/data/cru/)	Monthly	Not explicitly accounted for	Not explicitly accounted for	Yp or Yw estimated as the 90th percentile value within the range of actual yields for a similar climate class
	Ya derived from Monfreda et al. (2008)						
Foley et al. (2011)	Yp (no explicit difference with Yw)	Maize, wheat, rice, soybean, barley, millet, rye, sorghum, cassava, potato, sugarcane, sugar beet, groundnuts, oilpalm, rapeseed, cotton, sunflower	Gridded-interpolated average climate data for 1950–2000 from WorldClim: www.worldclim.org/	Average (50-y) monthly means	Not explicitly accounted for	Not explicitly accounted for	Yp or Yw estimated as the 95th percentile value within the range of actual yields for a similar climate class
	Ya derived from Monfreda et al. (2008)						
Mueller et al. (2012)	Yp and Yw (calculated as rainfed yield ceilings)	Maize, wheat, rice, soybean, barley, millet, rye, sorghum, cassava, potato, sugarcane, sugar beet, groundnuts, oilpalm, rapeseed, cotton, sunflower	Gridded-interpolated average climate data for 1950–2000 from WorldClim: www.worldclim.org/	Average (50-y) monthly means	Not explicitly accounted for, but statistically analyzed for sensitivity	Management to explain yield gap is described through a suite of climate- and crop-specific statistical input-yield models and rainfed yield ceilings.	Yp estimated as the 95th percentile value within the range of actual yields for a similar climate class
	Ya derived from Monfreda et al. (2008)						
Neumann et al. (2010)	Yp (no explicit difference with Yw)	Wheat, maize, rice	Gridded-interpolated average climate data for 1950–2000 from WorldClim: www.worldclim.org/	Average (50-y) monthly means	Applied soil fertility constraint is from Global Agro-Ecological Zones—2000 (http://www.iiasa.ac.at/Research/LUC/GAEZ)	Management to explain yield gap is included in the inefficiency function	Stochastic frontier production function is applied
	Ya derived from Monfreda et al. (2008)						
<i>Process-based approach to assess (sensitivity of) current yield</i>							
Liu et al. (2007)	Focused both on Yp or Yw, Ya and water productivity.	Wheat	Mix of actual weather-station (NCDC; www.ncdc.noaa.gov) and gridded-interpolated data (FAO CLIMWAT; http://www.fao.org/nr/water/infoceres.databases.climwat.html)	Mix of daily/monthly data	Soil parameters: depth and texture obtained from the Digital Soil Map of the World (DSMW; FAO), and from ISRIC-WISE data set (Batjes, 1995), with a 30' × 30' grid	Crop calendars (FAO), irrigation area and water use (AQUASTAT); average fertiliser use (FAOSTAT)	EPIC model coupled with GIS (Liu et al., 2007)
	Ya were simulated for the actual water and nutrient supplies and correlated well with the FAO statistics						

Appendix A (Continued)

Study	Explicit focus on Yp and Yw and source of Ya	Crops	Historical weather data		Soil data	Agronomic data	Crop model
			Source	Time step			
Stehfest et al. (2007)	Focussed on simulating Ya. These actual yields consider sub-optimal water and nitrogen supplies and are based on FAO.	Wheat, rice, maize and Soybean	CRU; New et al., 2000; www.badc.nerc.ac.uk/data/cru/	Monthly, interpolated to daily	Global Soil Data Task Group (2000) and FAO	Planting dates based on global monthly climate (New et al., 2000); nitrogen fertilizer derived from IFA (2002); irrigated area derived from Döll and Siebert (2000)	DayCent model (Stehfest et al., 2007)
Deryng et al. (2011)	Focus was on simulating Ya and effects of climate change, but an intermediate step was the estimation of Yp or Yw. Ya based on Monfreda et al. (2008)	Maize, soybean, spring wheat	CRU; New et al., 2002; www.badc.nerc.ac.uk/data/cru/	Monthly, interpolated to daily	ISRIC-WISE soil data available water capacity (Batjes, 2006)	Planting and harvesting algorithm based on global crop calendar (Sacks et al., 2010); irrigated cropland based on Portmann et al. (2010); fertilizer application based on IFA (2002)	PEGASUS model (Deryng et al., 2011)
<i>Process-based approach to assess yield potential</i>							
Penning De Vries et al. (1997), Luyten (1995)	Focus was on simulating Yp & Yw	Generic grain crop and grass crop	Ground-based weather stations from the dataset by Müller (1982, 1987); each grid cell has been linked to the nearest weather station	Monthly, interpolated to daily	Digitized soil data base from NASA (Zobler, 1986); suitability of soils for modern farming is based on criteria applied by FAO	Yp and Yw assume optimal management and maximal efficiency of resource use, not constrained by current management	LINTUL model (Penning De Vries et al., 1997)
Fischer et al. (2002)	Yp and Yw were simulated first and next, yield calculations were repeated with actual constraints such as losses by pests, diseases and weeds, losses by extreme climate conditions, etc.	154 crop, fodder and pasture land use types	CRU; New et al., 1998; www.badc.nerc.ac.uk/data/cru/	Monthly	FAO digital soil map of the world (DSMW, version 3.5); for the characterization of soil units: (a) FAO DSMW (FAO) and (b) WISE (Batjes, 1995; Batjes et al., 1997)	Agro-ecological characterization per grid unit to determine the start and length of growth cycles	Global agro-ecological zones (GAEZ) methodology is applied (Kassam, 1977; FAO)
Nelson et al. (2010) (IFPRI)	Yp, Yw and N-limited yields were simulated	Maize, winter wheat, rice, groundnut, and soybean	Gridded-interpolated (WorldClim; www.worldclim.org/)	Average (50-y) monthly means, interpolated to daily	FAO harmonized soil map of the world (Batjes et al., 2009)	Three sets of crop calen-dars have been developed for resp. rainfed crops, irrigated crops and spring wheat; N applications vary from 15 to 200 kg N/ha depending on crop, management system and country	DSSAT simulation model (Jones et al., 2003)
Müller* (Pers. Comm.; not based on any previous study but computed for this purpose)	Both Yp and Yw yields were simulated, Yp are yields with perfect irrigation, which does not exclude water stress in all cases.	Wheat, maize, rice, millet, sugarbeet, cassava, field peas, sunflower, groundnut, soybean, rapeseed, sugarcane	CRU TS 3.0; Mitchell and Jones, 2005; www.badc.nerc.ac.uk/data/cru/	Monthly, interpolated to daily (Sitch et al., 2003; Gerten et al., 2004)	Aggregated soil data based on Prentice et al. (1992)	Planting and harvest dates based on Waha et al. (2012)	LPJmL model (Bondeau et al., 2007; Fader et al., 2010; Waha et al., 2012)

* For the simulations a linear relationship was introduced between intercepted radiation and LAI for maize (Zhou et al., 2002) and it was assumed that maize reaches LAI = 5 under intensive management (compare Fader et al., 2010). Minimum winter wheat heat units was set to 2100 growing degree days and the minimum root fraction at maturity was set to 10% for both maize and wheat. Contrary to the description in Waha et al. (2012), here the rainfed sowing dates for irrigated (potential) yields were used.

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