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Yield gap analysis of field crops

Methods and case studies



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Yield gap analysis of field crops:

Methods and case studies

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Foreword

A world population that will exceed 9 billion by 2050 will require an estimated 60 percent more food. This increase means we need a major boost in current primary agricultural productivity. It is estimated that 80% of the required increase can stem from intensification. Achieving this production target without further large-scale conversion of land to agriculture requires higher crop intensification and greater annual crop productivity. However, crop productivity varies greatly from place to place, depending on environment, inputs and practices. Assessing the yield gap of existing cropped lands will indicate the possible extent of yield increase from actual values.

The authors of this publication provide a wide-ranging and well-referenced analysis of literature on current methods to assess productivity and productivity gaps of crops and cropping systems. “Potential” and “water-limited” yield are used to define current best attainable yields under irrigated and rain fed conditions, respectively, whereas “theoretical” yield represents the maximum yield that can be achieved according to current understanding of physiological principles of crop productivity, providing a guide to future increases in crop yield.

The methods for benchmarking yields and identifying yield-gaps are presented through a number of case studies, grouped into four approaches covering a range of applications. First, where actual levels of yield can be compared with attainable yields, there can be an immediate benefit to increase farm yield. Second, analysis of actual yields against environmental drivers provides insight into management possibilities to increase yield. It has particular application in rain fed systems where frontier analysis can identify seasons and conditions that support greatest water-limited yield and suggest management strategies and tactics to maximise water-productivity under the range of environmental conditions analysed. Third, crop models of various types, when used to provide independent benchmarks for potential and water-limited yield, can be extrapolated to areas of limited data availability, as it is currently the case for developing countries where the largest increases in food demand will occur. Fourth, large scale comparisons made by combining actual yield data with model estimates and remotely sensed information of crops and environment can inform about priority assessments and policy planning at regional and national scales.

Much work is needed to meet the challenge for greater food supply in the coming decades. The methods described here will form a basis for that work.



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Preface

On behalf of the Food and Agriculture Organization of the United Nations (FAO) and the Robert B. Daugherty Water for Food Institute at the University of Nebraska (DWFU), we are delighted to present this joint publication on “Yield gap analysis of field crops: Methods and case studies”. The publication reviews methods for yield gap analysis, clarifying definitions and techniques to measure and model actual, attainable and potential yield at different scales in space and time and uses case studies to illustrate different approaches. We see this publication as a significant contribution towards our respective efforts to advance global water and food security through improvements in water and land productivity.

Importantly, the publication provided critical input to, and benefitted from, the Expert Consultation on “Crop yield and water-productivity gaps: method, problems and solutions” that was co-hosted by FAO, DWFU and the Stockholm Environment Institute (SEI) in Rome on 3-4 October 2013. The Consultation brought together leading professionals to discuss methods to measure the gaps, as well as ways to diagnose the root causes of yield and water productivity gaps and the actions that will be needed to close yield gaps in both small and large scale cropping systems, including management options and policies to provide incentives for the adoption of gap-closing technologies.

This joint publication and the Expert Consultation are among the first results of a far-reaching agreement between FAO and DWFU signed by University of Nebraska President James Milliken and FAO Director General Jose Graziano da Silva in July 2012. The agreement calls for a collaborative program with three areas of focus: sustainably increasing crop yields and water productivity using modeling, remote sensing and information systems; improving drought management and climate adaptation; and improving sustainable production under drought, stress and water-limited conditions. The work on yield gap analysis is part of the first area of focus, and builds on the activities of FAO and the DWFU to develop tools and knowledge-delivery systems to inform and guide policymakers in managing water and agriculture and to identify areas with the greatest potential to increase food supply on a sustainable basis. In particular, it builds on two major initiatives: (i) the work of a team at the University of Nebraska and partner institutions to build a global Yield Gap Atlas; and (ii) the Regional Initiative on Water Scarcity for the Near East and North Africa Region providing tools and methods to increase water productivity in irrigated and rainfed systems.



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Summary

The challenges of global agriculture have been analysed exhaustively and the need has been established for sustainable improvement in agricultural production aimed at food security in a context of increasing pressure on natural resources.

Whereas the importance of R&D investment in agriculture is increasingly recognised, better allocation of limited funding is essential to improve food production. In this context, the common and often large gap between actual and attainable yield is a critical target.

Realistic solutions are required to close yield gaps in both small and large scale cropping systems worldwide; to make progress in this direction, we need (1) definitions and techniques to measure and model yield at different levels (actual, attainable, potential) and different scales in space (field, farm, region, global) and time (short, long term); (2) identification of the causes of gaps between yield levels; (3) management options to reduce the gaps where feasible and (4) policies to favour adoption of gap-closing technologies.

The aim of this publication is to review the methods for yield gap analysis, and to use case studies to illustrate different approaches, hence addressing the first of these four requirements.

Theoretical, potential, water-limited, and actual yield are defined. *Yield gap* is the difference between two levels of yield in this series. Depending on the objectives of the study, different yield gaps are relevant. The *exploitable yield gap* accounts for both the unlikely alignment of all factors required for achievement of potential or water limited yield and the economic, management and environmental constraints that preclude, for example, the use of fertiliser rates that maximise yield, when growers' aim is often a compromise between maximising profit and minimising risk at the whole-farm scale, rather than maximising yield of individual crops. The gap between potential and water limited yield is an indication of yield gap that can be removed with irrigation.

Spatial and temporal scales for the determination of yield gaps are discussed. Spatially, yield gaps have been quantified at levels of field, region, national or mega-environment and globally. Remote sensing techniques describes the spatial variability of crop yield, even up to individual plots. Time scales can be defined in order to either remove or capture the dynamic components of the environment (soil, climate, biotic components of ecosystems) and technology. Criteria to define scales in both space and time need to be made explicit, and should be consistent with the objectives of the analysis. Satellite measurements can complement in situ measurements.

The accuracy of estimating yield gaps is determined by the weakest link, which in many cases is good quality, sub-national scale data on actual yields that farmers achieve. In addition, calculation and interpretation of yield gaps requires reliable weather data, additional agronomic information and transparent assumptions.

The main types of methods used in yield benchmarking and gap analysis are outlined using selected case studies. The diversity of benchmarking methods outlined in this

publication reflects the diversity of spatial and temporal scales, the questions asked, and the resources available to answer them. We grouped methods in four broad approaches.

Approach 1 compares actual yield with the best yield achieved in comparable environmental conditions, e.g. between neighbours with similar topography and soils. Comparisons of this type are spatially constrained by definition, and are an approximation to the gap between actual and attainable yield. With minimum input and greatest simplicity, this allows for limited but useful benchmarks; yield gaps can be primarily attributed to differences in management. This approach can be biased, however, where best management practices are not feasible; modelled yields provide more relevant benchmarks in these cases.

Approach 2 is a variation of approach 1, i.e. it is based on comparisons of actual yield, but instead of a single yield benchmark, yield is expressed as a function of one or few environmental drivers in simple models. In common with Approach 1, these methods do not necessarily capture best management practices. The French and Schultz model is the archetype in this approach; this method plots actual yield against seasonal water use, fits a boundary function representing the best yield for a given water use, and calculates yield gaps as the departure between actual yields and the boundary function. A boundary model fitted to the data provides a scaled benchmark, thus partially accounting for seasonal conditions. Boundary functions can be estimated with different statistical methods but it is recommended that the shape and parameters of boundary functions are also assessed on the basis of their biophysical meaning. Variants of this approach use nitrogen uptake or soil properties instead of water.

Approach 3 is based on modelling which may range from simple climatic indices to models of intermediate (e.g. AquaCrop) or high complexity (e.g. CERES-type models). More complex models are valuable agronomically because they capture some genetic features of the specific cultivar, and the critical interaction between water and nitrogen. On the other hand, more complex models have requirements of parameters and inputs that are not always available. “Best practice” approaches to model yield in gap analysis are outlined. Importantly, models to estimate potential yield require parameters that capture the physiology of unstressed crops.

Approach 4 benchmarking involves a range of approaches combining actual data, remote sensing, GIS and models of varying complexity. This approach is important for benchmarking at and above the regional scale. At these large scales, particular attention needs to be paid to weather data used in modelling yield because significant bias can accrue from inappropriate data sources. Studies that have used gridded weather databases to simulate potential and water-limited yields for a grid are rarely validated against simulated yields based on actual weather station data from locations within the same grid. This should be standard practice, particularly where global scale yield gaps are used for policy decisions or investment in R&D. Alternatively, point-based simulations of potential and water-limited yields, complemented with an appropriate up-scaling method, may be more appropriate for large scale yield gap analysis. Remote sensing applied to yield gap analysis has improved over the last years, mainly through pixel-based biomass production models. Site-specific yield validation, disaggregated in biomass radiation-use-efficiency and harvest index, remains necessary and need to be carried out every 5 to 10 years.

1. Introduction

Progress in crop production derives from advances in breeding and agronomy, including improvements in the spatial and temporal arrangement of crops in farming systems. The interaction between breeding and agronomy is widely acknowledged as a major driver of enhanced production. For instance, dwarfing genes in cereals lead to physiological improvement in grain/stem partitioning of dry matter with direct consequences for yield, but also allowed higher rates of nitrogen fertiliser with reduced risk of lodging in comparison with older, taller cultivars. Importantly, grass herbicides were critical to capture the benefits of short-stature cereals in mechanised production systems. The development and adoption of productivity enhancing technology can be stimulated or hindered by political, economic, environmental and infrastructure factors, as illustrated in Figure 1. Notwithstanding their importance, these factors are outside the scope of this publication. Likewise, we do not discuss policies to deal with yield gaps (Sumberg, 2012).

The challenges of global agriculture have been analysed exhaustively and the need has been established for sustainable improvement in agricultural production aimed at food security in a context of increasing pressure on natural resources (Cassman 2012; Connor and Mínguez 2012). Of a total global land area of 13,000 Mha, arable land and permanent crops account for by 12%, permanent meadows and pastures for 26%, forests for 30% whereas 32% of this land is unsuitable for agriculture (FAO 2011). Analysis that accounts for suitability of remaining land for cropping and alternative land uses concludes that expansion of cropping land to 2050 is likely to be small. Globally, 15% of arable land is irrigated and currently accounts for 42% of all crop production; 7100 km³ of water are consumed annually to produce food globally whereas feeding the world population of around 9 billion by 2050 would require an additional 2100 km³ year (Sumberg 2012; Rockstrom *et al.* 2012).

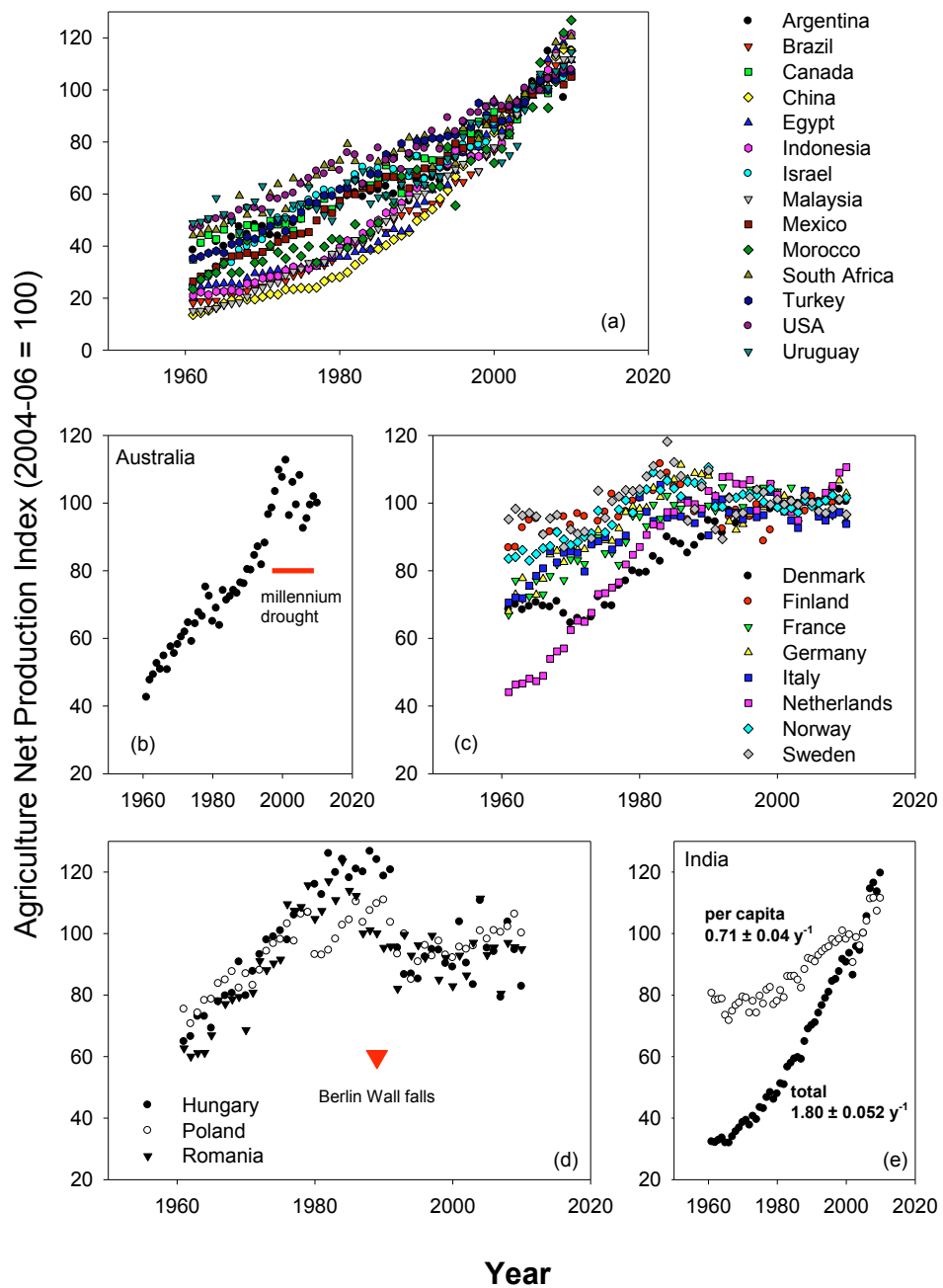
Whereas the importance of R&D investment in agriculture is increasingly recognised, better allocation of limited funding is essential to improve food production (Sumberg 2012; Connor and Mínguez 2012; Hall *et al.* 2013). In this context, the common and often large gap between actual and attainable yield is a critical target. Realistic solutions are required to close yield gaps in both small and large scale cropping systems world-wide; to make progress in this direction, we need:

1. Definitions and techniques to measure and model yield at different levels (actual, attainable, potential) and different scales in space (field, farm, region, global) and time (short, long term).
2. Identification of the causes of gaps between yield levels.
3. Management options to reduce the gaps where feasible.
4. Policies to favour adoption of gap-closing technologies.

In this context, the aim of this publication is to review the methods for yield gap analysis, and to use case studies to illustrate different approaches. Section 2 outlines the evolution of yield to highlight historical changes in the meaning of this term; this

FIGURE 1

(a) Time trends in FAO's Net Production Index (2004-2006 = 100) highlighting the sustained increase in productivity where infrastructure and policy favour development and adoption of technology. Examples of disruption in productivity caused by (b) drought in south-eastern Australia, where rainfall between 1997 and 2009 was 73 mm below average since the start of the 20th century (CSIRO, 2011); (c) European policies combined with climate and agronomic constraints; see for example Peltonen-Sainio *et al.* (2009) for a discussion of the effect of European policies on adoption of agricultural technologies in Finland and Brissson *et al.* (2010) for an account of recent yield stagnation in France; and (d) substantive changes in production systems triggered by changes in political systems in eastern Europe. (e) Highlights the sharp increase in total productivity against the slower improvement in productivity per capita where rates of population growth remain high in India.



leads to the definitions of yield used in this paper. Section 3 highlights the importance of explicit definitions of spatial and temporal scales in yield gap analysis, and discusses different data sources and their reliability. Desirable attributes of models in yield gap studies are discussed, including aspects of model structure, complexity, calibration, validation and input requirements. Section 4 is the core of this publication. It presents methods spanning a broad range of scales, complexities, input requirements and associated errors. Case studies include irrigated and rainfed crops in diverse cropping systems, from subsistence agriculture to high-input systems in North and South America, Africa, Europe, Asia and Oceania. Section 5 presents a summary and recommendations of methods for yield benchmarking and gap analysis.

2. Definitions of crop yield

2.1. EVOLUTION OF YIELD CRITERIA

Before agriculture, our ancestors were not unlike other animals, for which “yield” was the ratio between the energy derived from food and the energy invested in obtaining it. Once the sowing of crops was established as a common practice, the definition of yield shifted from an energy ratio to the ratio between the numbers of seed harvested and seed sown (Evans 1993). This was particularly important in low-yielding seasons, when early farmers had to make the hard decision of allocating seed for food or seed for the next sowing. An important consequence of this measure of yield was that selection favoured highly competitive plant types, i.e. abundant tillering/branching, large inflorescences, small grain and weak seed dormancy (Evans 1993). Only when availability of arable land came under pressure, mass of product per unit land area became a more important criterion.

This shift in definition of yield had a dramatic impact on selective pressures, shifting from the aggressive high-yielding plant (seeds per seed sown) to the less competitive “communal plant” able to produce more yield per unit area (Donald 1981). Evans (1993) envisaged the next measure of yield whereby the time dimension is considered explicitly, yield per ha per year. This measure is particularly important in the comparison of systems with contrasting cropping intensity, i.e. number of crops per year (Egli 2008; Cassman and Pingali 1995). Cassman and Pingali (1995) highlighted that the green revolution in rice had as much to do with increased cropping intensity as with increased harvest index and yield potential of semi-dwarf varieties. Thus, IR-8, the first modern rice cultivar, was much faster to mature than traditional rice land races it replaced (often by as much as 30–45 days) which allowed double rice cropping on irrigated land -now the dominant land use in rice-growing regions of South and Southeast Asia.

Increasing cropping intensity is widespread worldwide (Cassman and Pingali 1995; Farahani *et al.* 1998; Caviglia *et al.* 2004; Sadras and Roget 2004). In environments with favourable temperature and water availability, this involves a shift to multiple crops per year. This applies not only to the tropics, but also to temperate environments such as the Pampas of Argentina, where wheat-soybean double cropping is a dominant feature. In environments where rainfall or temperature prevents multiple cropping, such as dry environments of southern Australia, cropping intensity has been increasing at the expense of pastures. Thus, the concept of yield progress based on kg per ha will become inappropriate in some instances. Increasing cropping intensity could contribute to either stabilisation or decline in yield per crop. This was illustrated by Egli (2008), who reported an inverse relationship between rate of progress of yield of soybean crops and intensity of cropping measured as % of double crops in the system (Figure 2). Paradoxically, the best environments supporting higher cropping intensity showed the lowest rate of improvement in yield of individual crops.

Yield of individual crops, in kg per ha, is also inappropriate for comparisons of mainstream agriculture and organic production systems, as yield of individual crops does not account for the additional land, time, labour, and water cost of organic nutrients (Connor and Mínguez 2012). Meaningful comparisons of this kind must focus on the

whole production system, rather than individual crops.

Explicitly measuring yield per unit area and time is therefore of increasing importance. Where multiple cropping is prevalent, yield gap analysis should target the system and its components; Section 4.1.4 presents an example of gap analysis in wheat-maize double crops in China.

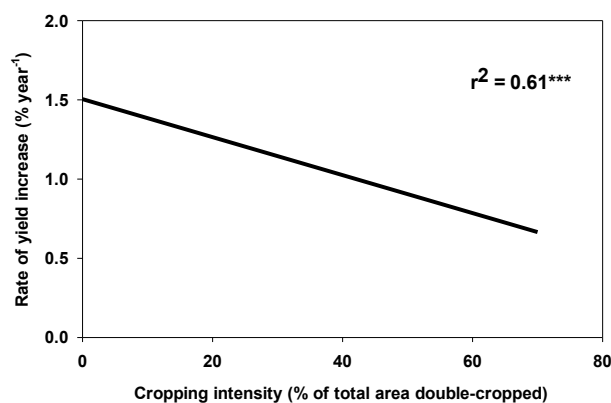
2.2. YIELD DEFINITIONS

This publication focuses on economic yield of desired plant products; be they grain, oilseed, tubers, corms, sugar, fibre, forage, or energy content. Yields of individual crops are in a continuum from crop failure to potential and several authors have proposed definitions to account for this range (van Ittersum and Rabbinge 1997; Evans and Fischer 1999; Connor *et al.* 2011). From these sources, here we list the definitions of yield relevant for yield gap analysis (Figure 3).

Theoretical yield is the maximum crop yield as determined by biophysical limits to key process including biomass production and partitioning. It can be estimated with models with sound physiological structure, and parameters reflecting the biophysical boundaries of key processes. This benchmark is perhaps more useful for breeding (Box 1); given its agronomic focus, this publication will not deal with theoretical yield.

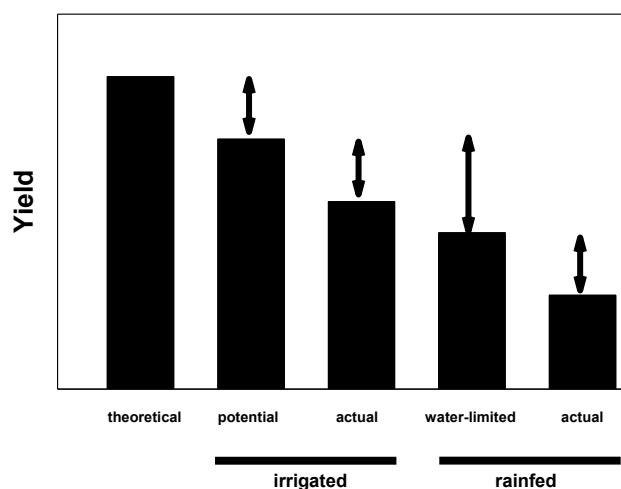
Potential yield (Y_p) is the yield of a current cultivar “when grown in environments to which it is adapted; with nutrients and water non limiting; and with pests, diseases, weeds, lodging, and other stresses effectively controlled” (Evans and Fischer 1999). Potential yield depends on location as it relates to weather but is independent of soil, which is assumed to be physically and chemically favourable for crop growth. The climate factors that influence potential yield are radiation, ambient CO_2 concentration and temperature (Evans and Fischer 1999; van Ittersum *et al.* 2013); photosynthesis, growth and potential yield are also responsive to fraction of diffuse radiation and vapour pressure deficit (Rodriguez and Sadras 2007). Potential yield is relevant to benchmark crops where irrigation, the amount and distribution of rainfall, or a combination of irrigation and rainfall ensure that water deficits do not constrain yield.

FIGURE 2
Decreasing rate of improvement of soybean yield in Kentucky (USA) with increasing cropping intensity, measured as percentage of wheat-soybean double cropping.



Source: Adapted from Egli (2008).

FIGURE 3
Definitions of yield relevant to yield gap analysis; arrows illustrate some yield gaps.



Source: Multiple sources (Bingham 1967; van Ittersum & Rabbinge 1997; Evans and Fischer 1999; Lobell *et al.* 2009; Connor *et al.* 2011).

BOX 1

THEORETICAL YIELD

The biophysical boundaries of yield are important, for example, when we ask questions about the value of improved crop photosynthesis – What is the gap between current photosynthesis and the biological limit of this trait? What is the expected impact of enhanced photosynthesis on crop yield? (Parry *et al.* 2011).

Models like APSIM, CERES, CropSyst or SUCROS (Section 3.3) could be used to estimate theoretical yield. However, these models are normally parameterised against the *actual* crop phenotype (Lindquist *et al.* 2005), and therefore do not necessarily capture the biophysical boundaries of important processes such as photosynthesis. Thus, models to calculate theoretical yield need not only plausible physiological and agronomic assumptions but also parameters that capture these boundaries; this requires a theoretical approach.

Attempts have been made to establish an upper boundary for daily net production of biomass from biophysical principles (Connor *et al.* 2011; Loomis and Amthor 1999) and, separately, for the biological limit of harvest index (Foulkes *et al.* 2009). The lack of independence between production and partitioning of biomass (Körner 1991) and trade-offs, for example between further increase in harvest index and lodging (Foulkes *et al.* 2011), are some of the many constraints to scale up from low levels of organisation and short time steps to seasonal growth and yield (Connor and Fereres 1999). Theoretical yield can therefore be derived from basic principles in two ways: modelling yield from the bottom up, or estimating the upper limit of key parameters such as radiation use efficiency, and use these theoretical parameters in crop-level models.

Theoretical yield is constrained by genotypic (e.g. canopy architecture, harvest index) and environmental drivers of crop development, growth and resource partitioning in non-stress conditions. Recognised environmental factors include solar radiation, ambient CO₂ concentration, temperature and photoperiod, as they modulate development and growth (Fischer 1985; Slafer *et al.* 2009). More recently, the list of environmental factors has been expanded to include proportion of diffuse radiation and vapour pressure deficit (Rodriguez 2007). For a given amount of radiation, photosynthesis increases with the proportion of diffuse radiation, that depends on atmospheric conditions and canopy traits (Spitters 1986; Sinclair and Shiraiwa 1993b; Roderik and Farquhar 2003). Stomatal conductance and photosynthesis decline with high vapour pressure deficit even in well-watered plants including irrigated rice and wetland species (Otieno *et al.* 2012; Ohsumi *et al.* 2008). Latitudinal gradients of both diffuse radiation and vapour pressure deficit have been described for the wheat-belt of eastern Australia, which account for part of the latitudinal gradients of crop yield potential (Rodriguez and Sadras, 2007).

Water-limited yield (Y_w) is similar to yield potential, except that yield is also limited by water supply, and hence influenced by soil type (water holding capacity and rooting depth) and field topography. This measure of yield is relevant to benchmark rainfed crops.

Attainable yield is the best yield achieved through skilful use of the best available technology. Some studies use attainable yield as an approximation to either potential yield or water-limited yield (Hall *et al.* 2013).

Actual (Y_a) reflects the current state of soils and climate, average skills of the farmers, and their average use of technology.

Yield gap is the difference between two levels of yield. Depending on the objectives of the study, different yield gaps are relevant (Figure 3). The *exploitable yield gap* accounts for both the unlikely alignment of all factors required for achievement of potential or water limited yield and the economic, management and environmental constraints that preclude, for example, the use of fertiliser rates that maximise yield, when growers' aim is often a compromise between maximising profit and minimising risk at the whole-farm scale, rather than maximising yield of individual crops (Box 2). To account for this, a factor (< 1) is used to scale yield potential and water-limited yield. A factor = 0.8 has been used in extensive production systems; higher factors may apply for high-value horticultural crops, and smaller factors in other systems depending on technological and economic (e.g. grain price) drivers.

BOX 2

MAXIMISING YIELD AND WATER PRODUCTIVITY – DOES IT MAKE SENSE?

The notion that yield and water productivity can be “optimised” provides a sound working hypothesis when we ask questions about the best combination of resources (land, water, nutrients, radiation, labour, capital). In real production settings, however, the maximum output (yield, water productivity) is rarely the best strategy as it may require cropping practices that are economically unsound or too risky in economic and environmental terms. To illustrate this point, we present two examples of trade-offs: between the efficiency in the use of water and nitrogen, as related to nitrogen supply in rice and maize, and between water productivity and yield of rice, as related to water regime.

Nitrogen-driven trade-off between water productivity and the efficiency in the use of nitrogen

High water productivity requires adequate nitrogen supply. However, the relationship between yield and nitrogen supply conforms to the law of diminishing returns, and therefore nitrogen use efficiency declines with increasing nitrogen supply. The effect of individual inputs such as water and nitrogen on the carbon, water and nitrogen budgets of crops thus determines a nitrogen-driven trade-off between water productivity and nitrogen use efficiency (Sadras and Rodriguez 2010). This is illustrated for aerobic and flooded rice in the Philippines and for rainfed and irrigated maize in the USA (Fig. Box 2-1).

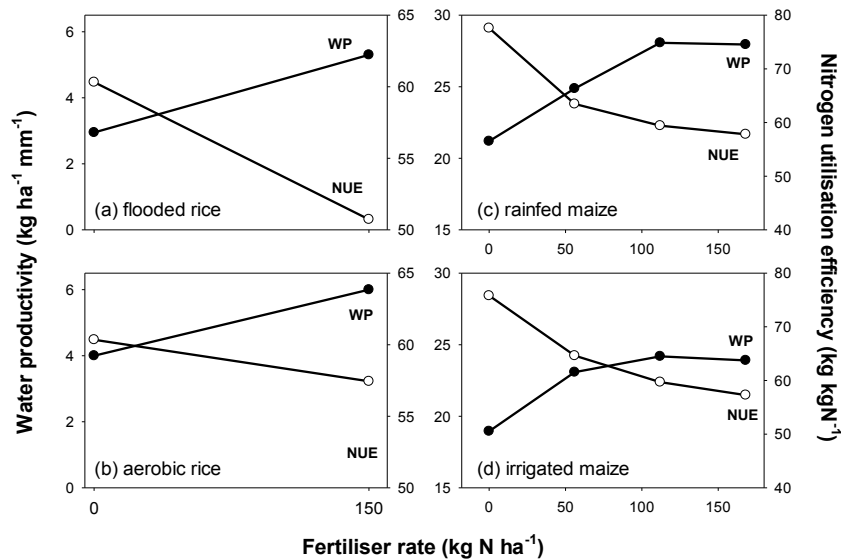
Thus, maximising water productivity in some farming systems may require nitrogen rates that are too costly, too risky or environmentally unsound. This is particularly important with high fertiliser-to-grain price ratio, in environments prone to nitrogen leaching, or where biophysical, social, economic or infrastructure factors constraint the use of fertiliser.

Water-regime driven trade-off between rice yield and water productivity

Bouman *et al.* (2006) and Farooq *et al.* (2009) reviewed the water productivity of rice, of which about 90% is produced in irrigated or rain-fed lowland fields (“paddies”). Water for lowland rice needs to account for land preparation requirements, seepage, percolation, evaporation and transpiration. Combined seepage and percolation, for example, range from 1-5 mm d⁻¹ in heavy clay soils to a massive 25-30 mm d⁻¹ in sandy and sandy-loam soils (Bouman *et al.* 2006). In a context of water scarcity, water saving technologies are being explored to reduce water use and improve water productivity, including aerobic rice and alternate wetting and drying. The principle underlying these techniques is the increase in water productivity associated with reduced water input. However, water saving techniques can also reduce grain yield.

FIGURE BOX 2-1.

Nitrogen driven trade-off between water productivity and nitrogen utilisation efficiency in (a) flooded and (b) aerobic rice in the Philippines, and (c) rainfed and irrigated maize in USA. Water productivity is yield per unit irrigation + rainfall (a,b) or yield per unit evapotranspiration (c,d). In all cases nitrogen utilisation efficiency is grain yield per unit nitrogen uptake (excluding root N).



Source: (Belder *et al.* 2005; Kim *et al.* 2008)

Comparison of rice crops grown under aerobic and flooded conditions in tropical environments of the Philippines (14° N) showed a substantial increase in water productivity at the expense of grain yield (Fig. Box 2-2). In relation to the flooded regime, aerobic culture increased average water productivity from 5.7 to 7.4 kg grain ha⁻¹ mm⁻¹ and reduced yield from 6.4 to 5.7 t ha⁻¹. In contrast, aerobic rice crops in temperate environments of Japan (34-35° N) outperformed their flooded counterparts in terms of water productivity (average 8.3 vs. 3.4 kg grain ha⁻¹ mm⁻¹) and showed no yield penalty (average 8.6 vs. 8.1 t ha⁻¹) (Kato *et al.* 2009).

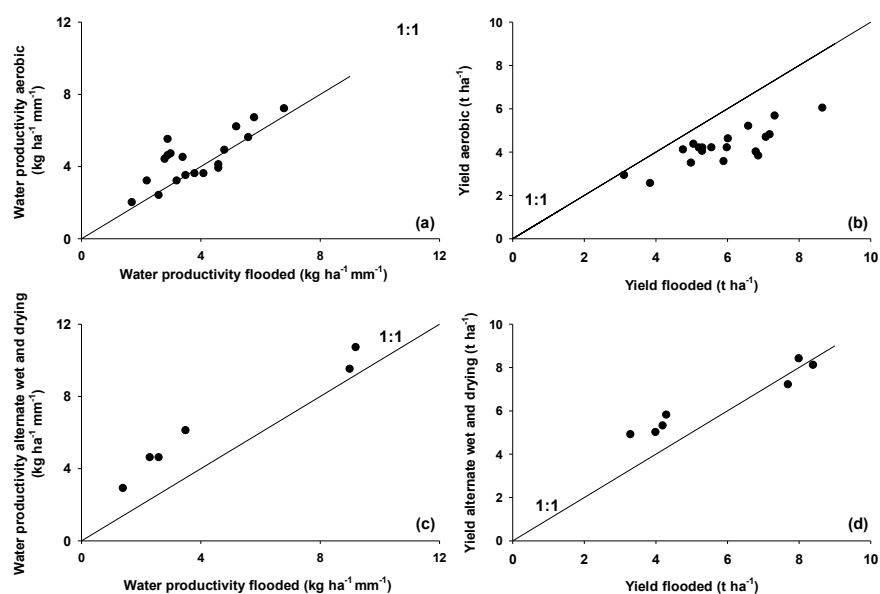
For a large number of crops in central-northern India and Philippines, alternate wetting and drying improved water productivity of rice in comparison with the flooded checks, but yield penalties up to 70% were recorded. Further studies in lowland rice areas with heavy soils and shallow (0.1-0.4 m) groundwater tables in China and Philippines showed that alternate wetting and drying outperformed their flooded counterparts in terms of water productivity (Fig. 3c) with no associated yield penalties (Fig. 3d). In all these cases, extremely shallow groundwater tables allowed for ponded water depths that were typically within the root zone during the drying periods (Bouman *et al.* 2006).

In summary, cultural practices to improve water productivity are obviously desirable, but need to be seen in the broader context of agronomic, economic and environmental trade-offs. Some trade-offs are inherent to the biophysical features of cropping systems, and cannot be broken. The nitrogen-driven trade-off between water and nitrogen productivity belongs to this category. This type of trade-off may lead to practices that do not necessarily maximise water productivity, but rather account for multiple objectives: lower rates of nitrogen fertiliser and associated low water productivity may be justified in terms of reduced economic and environmental risk.

The trade-off between yield and water productivity associated with water saving techniques can be broken in some instances, as illustrated in Fig. Box 2-2. Water saving techniques that improve water productivity at the expense of grain yield can be justified in some cases, but research should be encouraged to identify the conditions

FIGURE BOX 2-2.

(a) Aerobic rice had similar or greater water productivity and (b) lower yield than rice grown under a flooded regime in the Philippines. (c) Alternate wetting and drying improved rice water productivity and (d) caused no yield penalties in comparison with the flooded checks in the Philippines and China.



Source: (Bouman *et al.* 2005; Bouman *et al.* 2006).

The gap between potential and water limited yield is an indication of yield gap that can be removed with irrigation. For example, modelling studies in cropping systems of Bolivia compared yield of rainfed quinoa, from 0.2 to 1.1 t ha⁻¹, with yield under irrigation aimed at avoiding stomatal closure during all sensitive growth stages from 1.5 to 2.2 t ha⁻¹, thus representing gaps around 1.2 t ha⁻¹ (Geerts *et al.* 2009). Yield responses to irrigation for major annual and perennial crops have been recently reviewed by FAO (Steduto *et al.* 2012).

In addition to yield gaps outlined in Figure 3, other yield gaps can be defined that, for example, compare different cropping technologies such as nutrient management (Section 4.1.2) and irrigation regimes (Section 4.3.4).

3. Scales, data sources and overview of methods

Yield gaps can be quantified at different scales in space and time (Hall *et al.* 2013). Hence, the accuracy and precision^a of basic data for yield gap analysis need to be considered in relation to the target spatial and temporal scale. Spatially, yield gaps have been quantified at levels of field e.g. (French and Schultz 1984b), region e.g. (Casanova *et al.* 1999), national or mega-environment e.g. (Caldiz *et al.* 2002) and globally e.g. (Licker *et al.* 2008). Variation of yield within fields is the focus of site-specific management (Cassman 1999). No attempt has been made, however, to capture within-field variation in yield gap analysis.

Some yield gap studies do not make explicit assumptions about time scale, some have explicitly used time series that are long enough to span a wide weather range but short enough to meet the assumption of constant technology, and some have explicitly used time series to characterise time-trends in yield gaps. In addition to the accuracy of yield data, reliable weather data, additional agronomic information and transparent assumptions are essential for calculation and interpretation of yield gaps, as discussed in the next Sections.

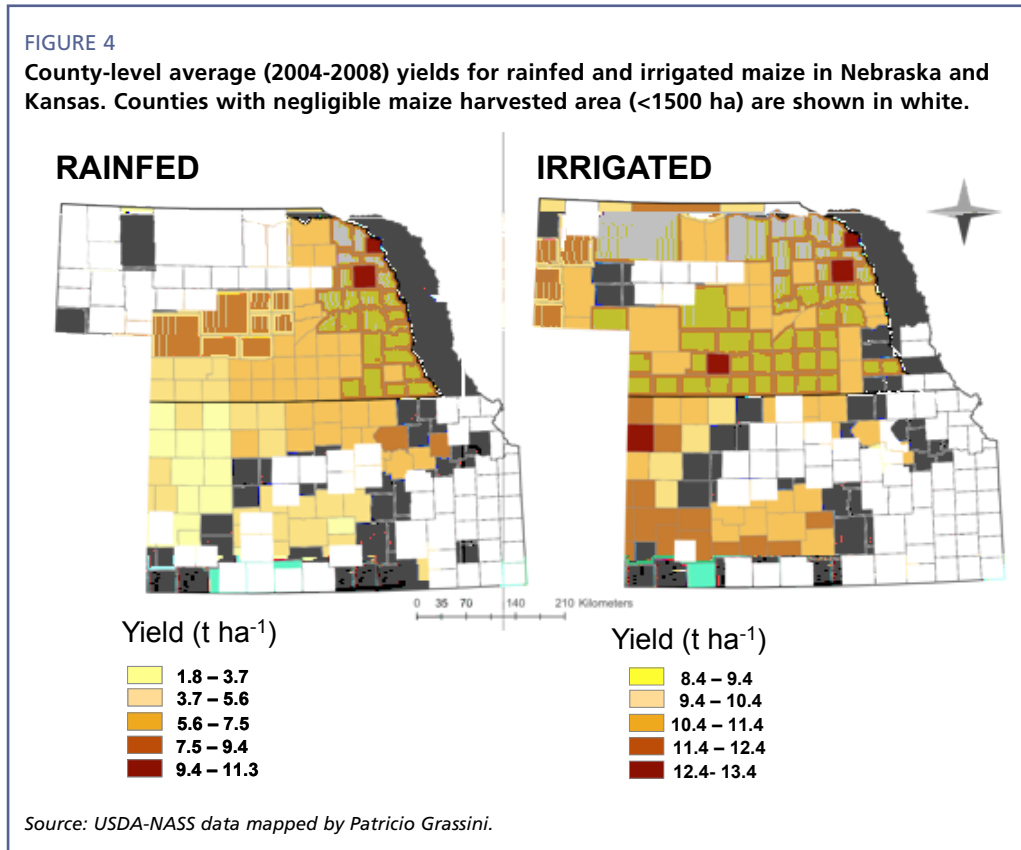
3.1. ACTUAL YIELD DATA: SPATIAL SCALES AND ACCURACY

The accuracy of estimating yield gaps is determined by the weakest link, which in many cases is good quality, sub-national scale data on actual yields that farmers achieve (Van Ittersum *et al.* 2013). Monfreda *et al.* (2008) and You *et al.* (2009) comprehensively reviewed yield data availability. There are three main levels of spatial resolution at which actual yield data can be available:

- (i) First-level administrative units: district, region, province, country.
- (ii) Second-level administrative units: municipality, county, sub-district.
- (iii) Farmer-reported data or data collected through surveys from relatively smaller areas.

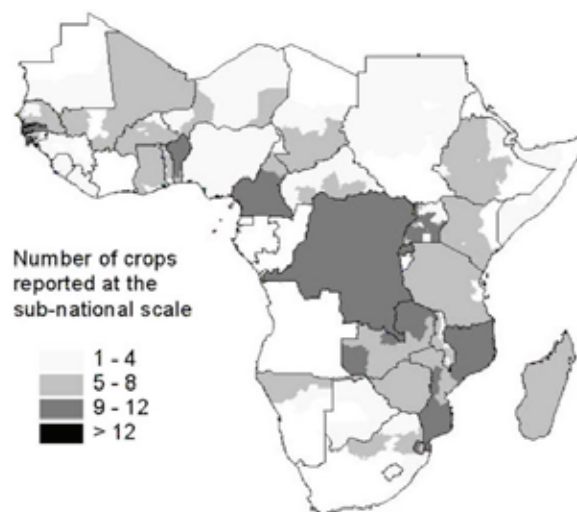
Current global yield databases are mostly based on data around year 2000 reported in the Agro-Maps (FAO *et al.* 2006; FAO 2012) for the first and, sometimes second, levels of administrative units complemented with interpolation methods to achieve full spatial coverage (Monfreda *et al.* 2008; You *et al.* 2009). More accurate geospatial distribution of current crop yields and their spatio-temporal variability are needed and yields of irrigated and rainfed crops must be distinguished within administrative units where both forms of production exist. An example of this kind is the USDA-NASS database where long-term (30+ years) county-level yield data are available, separately for each crop species, under each water supply regime, as illustrated for maize in Figure 4. Importantly, a good understanding of local conditions is essential to avoid data misinterpretation; e.g. owing to the “millennium drought”, yield maps around year 2000 are a biased snapshot for production systems of Australia (Figure 1).

^a See *Glossary* for definitions of this and other terms.



Many countries where yield-gap analysis is urgently needed have no data at the second, or even first, spatial level (Monfreda *et al.* 2008; You *et al.* 2009). For example, You *et al.* (2009) reported that only a few Sub-Saharan Africa countries (Benin, Cameroon, D.R. Congo, Uganda, Zambia, Mozambique) have more than 10 crops with yields reported at sub-national scale, that is, at the district, region, or province level (Figure 5). For other countries (Angola, Republic of Congo, Gabon, Ivory Coast) production data are only available at the country level. Cowpea, bean, maize and cassava have the most complete sub-national data coverage, with data for over 70% of total sub-national units. Over all crops and countries in Sub-Saharan Africa, there is an approximately 40% coverage of sub-national data. Sub-national data (municipality, county, or sub-district) are not currently available for most Sub-Saharan Africa countries. Another problem is that, in many countries, average yields are not crop-specific, that is, they are only reported for aggregate crop categories such as 'grain', 'fruit', 'pulses', and 'vegetables' (Monfreda *et al.* 2008). Some projects are currently underway to achieve greater spatial resolution and specificity with regard to crop species; such as Global Futures (<http://globalfuturesproject.com/>) and

FIGURE 5
Sub-national (district, region, province) data coverage in Sub-Saharan Africa.



Source: You *et al.* (2009).

construction of a number of household panel survey datasets are in progress at several international agricultural research centres.

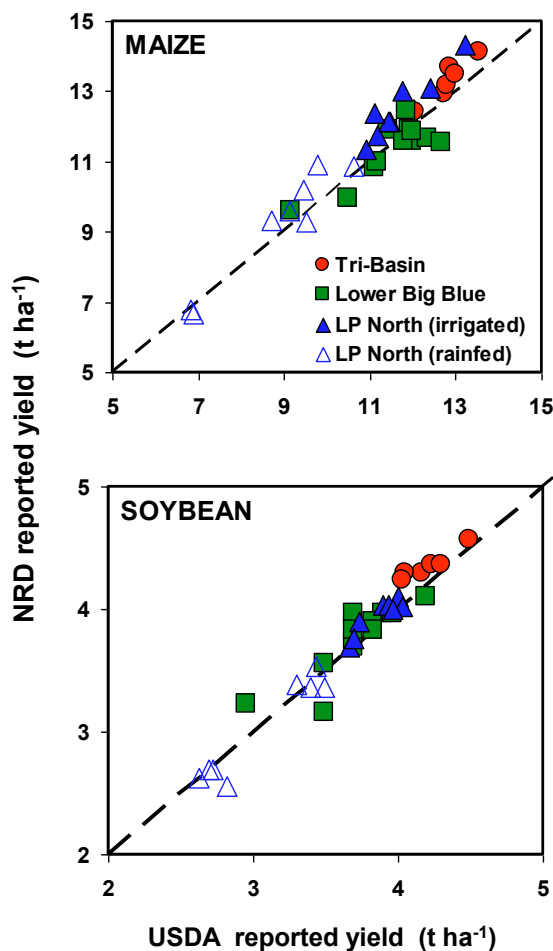
Because national and sub-national yield averages are based, in many countries, on estimates and surveys, the accuracy of reported yield should be evaluated by comparison against independently collected data and direct on-farm measurements and monitoring. For example, Wairegi *et al.* (2010) found the FAO-reported country-level average banana yield for Uganda of 5.5 t ha⁻¹ (by year 2007) underestimated measured yield in control plots of a nationwide on-farm trial conducted in the same year, in

which yield averages ranged from 9.7 to 20 t ha⁻¹ across major producing areas. In a broader analysis, Tittonell and Giller (2013) compared two sources of yield data for several crops in eastern and southern Africa. They concluded that, despite its wide coverage, FAO's national average yield was close to the mid-range yield reported in the scientific literature for maize, sorghum, millet and some grain legumes. In contrast, the FAO average yield for cassava and highland banana was closer to the lower end of the yield range found in the literature.

Kim and Dale (2004) compared yield of cereals and sugarcane from two sources, FAOSTATS and national databases, for a number of countries between 1997 and 2001. The two sources were in close agreement for all reported crops in Canada and USA (difference below 1%). Large mismatches were found for Mexico (up to 33% for oats) and for rice in Japan, Korea and Mexico ($\geq 25\%$). Despite some uncertainties, the FAO database provides long-term time series for most crops and countries that are otherwise unavailable or difficult to obtain (Tittonell and Giller 2013; Kim and Dale 2004).

Grassini *et al.* (unpublished) found good agreement between county-average yield for soybean and corn reported by USDA-NASS and average yields estimated from farmer-reported data in three Nebraska Natural Resources Districts located in the same counties, in the same years (Figure 6). USDA-NASS average yields are based on harvested yields, reported by a sample of farmers within each county, verified with independent yield samples taken by USDA staff when the crop reaches maturity. For the Natural Resources Districts in Nebraska, all farmers within the reporting areas send their crop yield reports to the local district office together, in many cases, with yield maps

FIGURE 6
Comparison between average farmer-reported Natural Resource District (NRD) in Nebraska, USA, and USDA-NASS county-level average maize and soybean yields (upper and bottom panels, respectively).



Data include three NRDs: Tri-Basin (2005-2010), Lower Platte (LP) North (2004-2011), and Lower Big Blue (2000-2011). Irrigated and rainfed crops in the LP North NRD are indicated with solid and open symbols, respectively. Note that no data on rainfed yields are available for the Tri-Basin and Lower Big Blue NRDs. Dashed lines indicate 1-to-1 line.

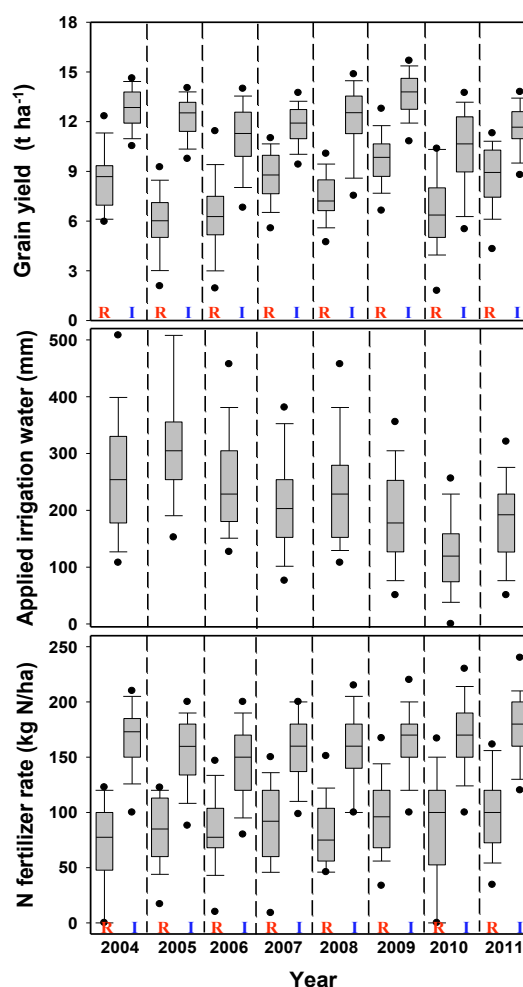
Source: Grassini *et al.* (unpublished).

and elevator tickets. These independent quality-control checks can help identify problems and improve the method to estimate and report actual yields.

Comparisons of databases of wheat, soybean and maize acreages and yields estimated by a pair of independent organisations in Argentina (Ministerio de Agricultura vs. *BC*, Bolsa de Cereales de Buenos Aires) indicated a high degree of consistency between data sources, as reflected in high correlation coefficients (i.e. high precision) (Sadras *et al.* 2013b). However, a significant mismatch between sources was found that was inversely proportional to acreage. This means that for some applications, for example calculation of relative rate of progress in grain production, both data sources would return statistically equivalent results. This is not the case for questions requiring accuracy, such as estimates of actual regional production.

Local yield gap analysis can also benefit from data collected through government and industry organisations, including growers marketing cooperatives. As regulatory pressures on environmental performance of agriculture increase (e.g., water quality, endangered species, greenhouse gas emissions), the standard and requirements for farmer reporting is likely to increase. For example, the national organisation of New Zealand's grape and wine sector requires for all members to complete their annual survey as a condition for accreditation for the Sustainable Winegrowing New Zealand program (Campbell 2013). This leads to greater availability of high quality yield, acreage and input data (fertilisers, irrigation amount, pesticides, etc), which provides opportunities to quantify impact of management practices on yield and efficiencies of water and nutrients as a complement to high-cost, multi-year, multi-site field studies e.g. (Grassini *et al.* 2011). A pre-condition is that on-farm yield data must be of sufficient detail and quality (i.e. include field location, water regime and other significant agronomic information) and capture a representative population of farmers over several cropping seasons. Accuracy of farmer-reported data can be assured when complemented with yield maps, elevator tickets, etc., and/or validated against other independent sources of yield data for the same region. The farmer-data reporting system of the Nebraska Natural Resources Districts is an example of a high-quality database that includes field-specific information on yield and inputs across many fields over many years (Figure 7). Data reported by a popula-

FIGURE 7
Box-plots of farmer-reported maize yield, applied irrigation, and N fertiliser during the 2004-2011 interval in the Lower Platte North Natural Resource District in Nebraska (USA) for irrigated (I) and rainfed (R) maize.

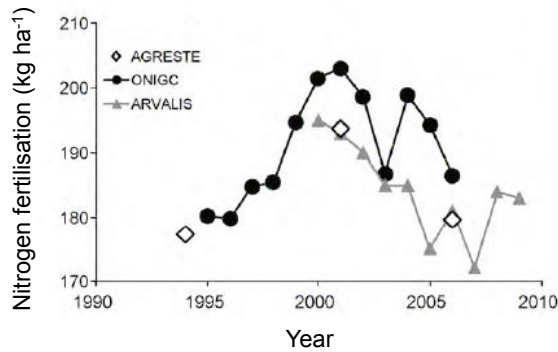


Box plots indicate: median (horizontal lines), 25 and 75 percentiles (box), 10 and 90 percentiles (bars), and 5 and 95 percentiles (solid circles). Average number of observations, across years, was 400 and 50 for irrigated and rainfed maize crops, respectively.

Source: Grassini *et al.* (unpublished).

FIGURE 8

Dynamics of nitrogen fertilisation in France according to three sources: AGRESTE (Statistical Service of the French Ministry of Agriculture), ONIGC (French National Office of Arable Crops), and ARVALIS (French Technical Institute for Cereal Crops).



Source: Brisson et al. (2010)

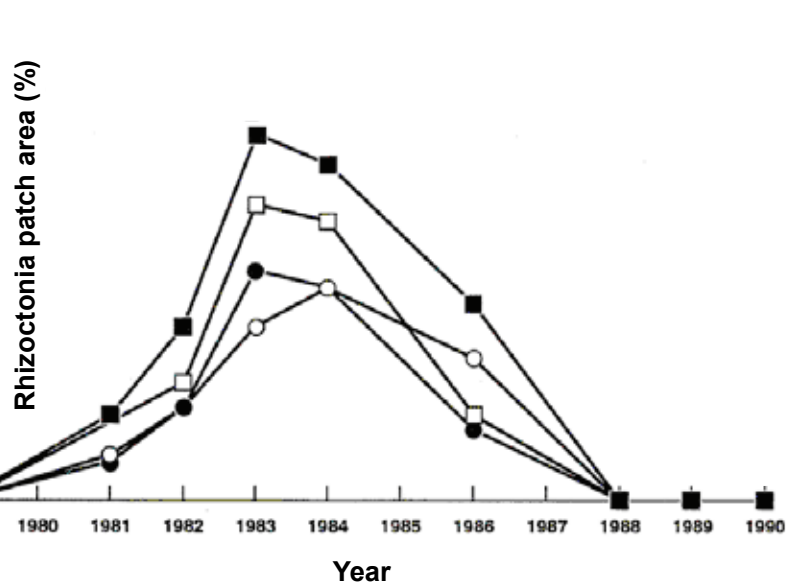
tion of farmers allow analysis of variation in yield and input-use efficiency across farms. Furthermore, when these data are complemented with more detailed data on crop, soil, inputs and management practices (e.g., tillage, irrigation scheduling, sowing date), they can help to identify region-specific sets of management practices that give highest yields and input-use efficiencies with lowest risk (Grassini and Cassman 2012).

As with yield, the reliability of other important data such as fertiliser use depends on source and scale. Figure 8 illustrates the discrepancy in nitrogen fertilisation rates in France among three sources. Irrespective of the source of data, a good understanding of the farming system is important to reduce likelihood of artefacts and misinterpretation of data. To illustrate this point, Figure 9 shows the dynamics of rhizoctonia bare patch caused by *Rhizoctonia solani* Kühn

AG-8 in wheat crops after the establishment of direct drill. Under South Australian conditions, impact of the disease peaks after 5–6 years from implementation of direct drill technology, and decreases afterwards with the development of disease-suppressing microorganisms in the soil (Roget 1995). In this scenario, sampling for yield in 1983–84 would have returned larger yield gaps than after 1988. The example in Figure 9 applies to individual fields; at regional level, spread of adoption of direct drill could lead to different patterns, highlighting again the importance of scale. The

FIGURE 9

Dynamics of rhizoctonia root rot in direct-drilled wheat crops in South Australia. Wheat was grown in rotation with volunteer pasture (closed square), pea (closed circle), medicago (open circle) or in monoculture (open square). Error bars are lowest significant difference ($P=0.05$).



Source: Roget (1995)

next Section summarises approaches able to deal with this type of variation and Section 3.3.3 expands on the importance of cropping system context for modelling aspects of yield gap analysis.

3.2. TEMPORAL SCALES

The approach used to define time scale for yield gap analysis depends on the objectives of the study, but the assumptions must be transparent and consistent with the requirements for critical interpretation of results. Time scales can be defined that either remove or capture the dynamic components of the environment (soil, climate, biotic components of ecosystems) and technology. Over time for example, pathogens and weeds can build up gradually, temperature can increase, rainfall decline and soil nutrients can be depleted; all these trends could lead to increasing yield gaps. Changes in the opposite direction, e.g. establishment of disease suppression microorganisms (Figure 9) can contribute to narrowing gaps over time. We assume that effects of other drivers of crop production, including shifts in markets and policy, are mediated by development and adoption of technology (Figure 1).

3.2.1. Removing the dynamic components of environment and technology

The number of years required to estimate actual yield is a compromise between a time series that is long enough to capture variation in weather, and short enough to avoid trends associated with technological and environmental change (van Ittersum *et al.* 2013; Calviño and Sadras 1999). van Ittersum *et al.* (2013) illustrate this balance for irrigated maize in Nebraska and a favourable environment for rainfed wheat production in The Netherlands (Figure 10). In both cases, yields from the five most recent years were enough to obtain estimates of the average yield and the coefficient of variation that are similar to those obtained with yields from the last 10 years. In harsh environments for rainfed crop production, 10 years is needed for Nebraska and even more are needed for Australia. Less than five years in these harsh production environments leads to biased estimates of average yield and coefficient of variation through the influence of years with exceptionally high or low seasonal rainfall. Finally, note that a longer time interval (20 years) may bias the estimates of average yield and coefficient of variation due to the technological change, i.e. improved varieties and agronomy, and to a lesser extent changes in climate, as shown for irrigated and rainfed maize in Nebraska and wheat in The Netherlands.

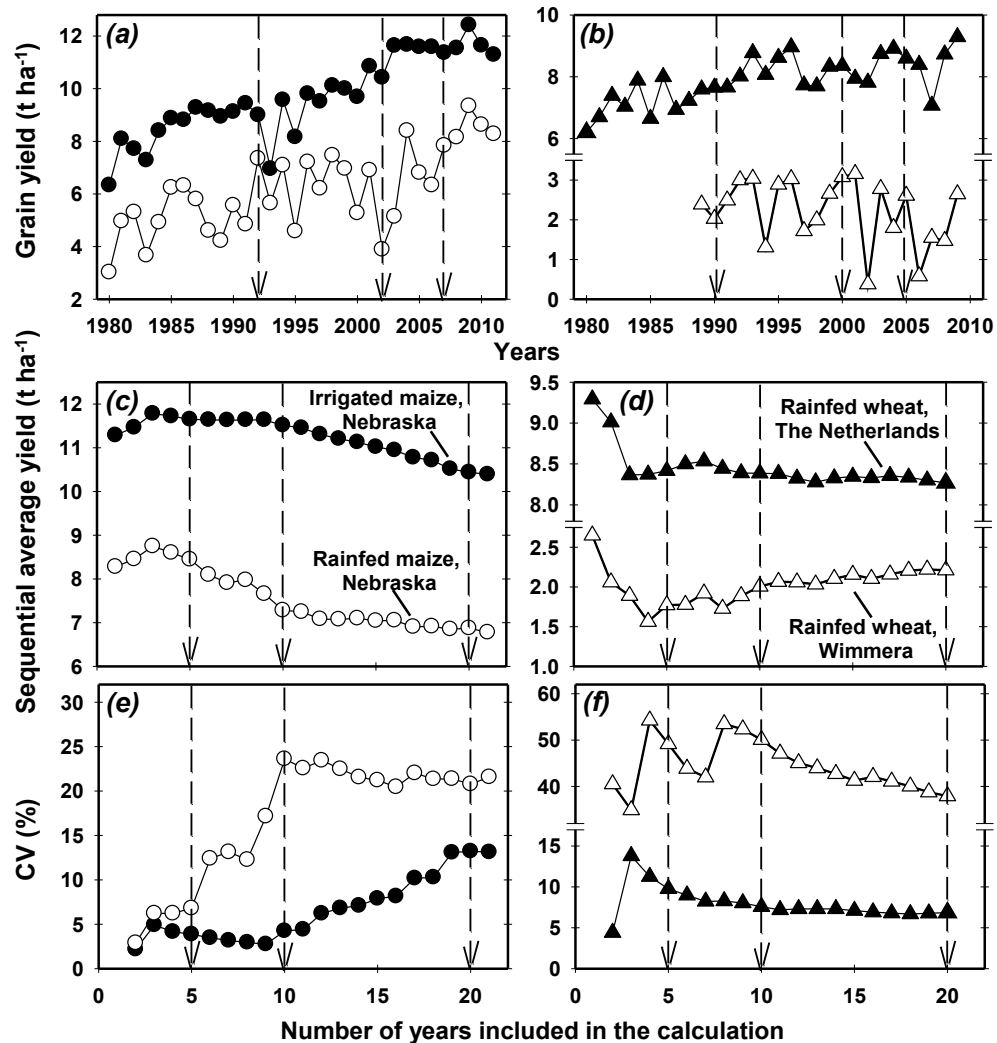
3.2.2. Capturing the dynamic components of environment and technology

The second approach to deal with time series is to explicitly quantify the changes in yield gaps over time. Laborte *et al.* (2012) presented a dynamic view of yield gaps accounting for the differential rate of yield progress through time. It revealed that Philippine rice growers in the upper quantiles improved yield much faster than growers in the lower quantiles, hence broadening the yield gap with time (Figure 11). Section 4.3.2 presents further details of this study.

Bell and Fischer (1994) compared actual and modelled wheat yield in the irrigated Yaqui Valley of northwestern Mexico between 1968 and 1990 (Figure 12). Actual yield increased linearly at a rate of $57 \text{ kg ha}^{-1} \text{ y}^{-1}$. Modelled yield accounting for weather-based potential yield declined at $46 \text{ kg ha}^{-1} \text{ y}^{-1}$; this was putatively associated with a

FIGURE 10

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 in (c) Nebraska, (d) The Netherlands and Wimmera, and associated coefficients of variation for (e) Nebraska, and (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 coefficients of variation.

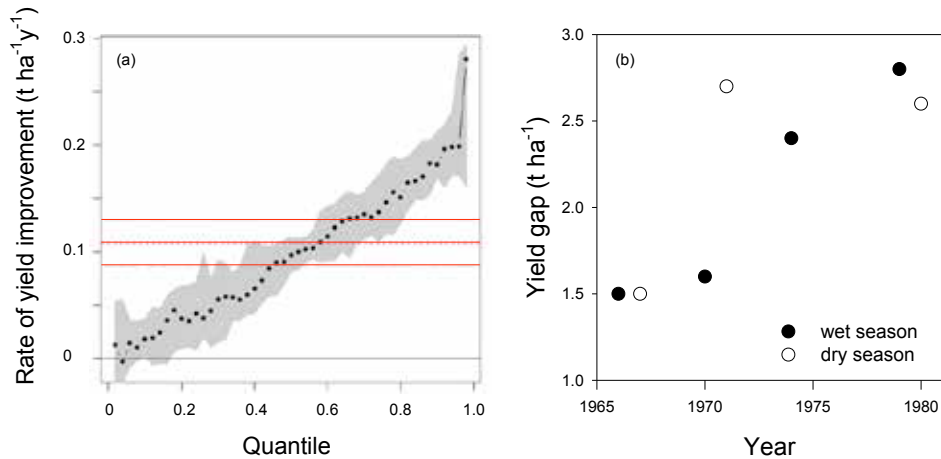
Source: van Ittersum et al. (2012).

mild warming trend over the period. The gap between actual and modelled yield thus declined at 103 kg ha⁻¹ y⁻¹. Using this dynamic perspective, the authors concluded that allowance for the temporal temperature change showed that the returns from improved crop management and breeding were superior to those suggested by the increase in actual yield.

Van den Berg and Singels (2012) compared actual yield records and simulated yield potential of sugarcane in five agroclimatic regions of South Africa. The gap between

FIGURE 11

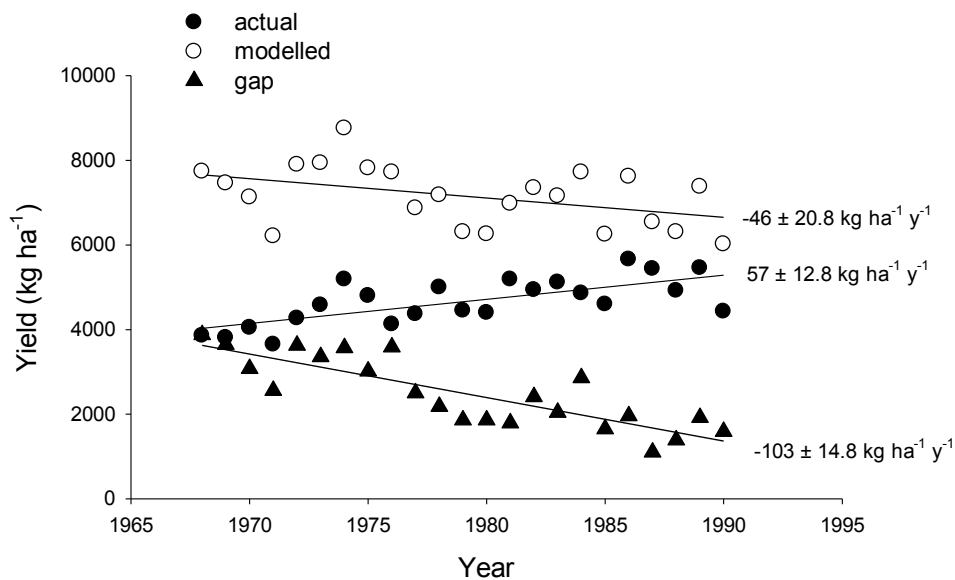
(a) The rate of rice yield improvement between 1966 and 1979 in Central Luzon (Philippines) was much larger for growers in the top quantiles than for those in the lower quantiles. As a consequence the gap between the yield of best and average farmers (b) almost doubled during this period. In (a) the red lines represent the ordinary least squares estimate and the 90% confidence interval of the estimate. The gray area refers to the 90% confidence band for the quantile regression estimates.



Source: Laborte et al. (2012).

FIGURE 12

Time trends in actual and modelled yield, and yield gap of wheat in the irrigated Yaqui Valley of northwest Mexico between 1968 and 1990. Modelled yields are estimates with CERES-Wheat, assuming no change in cultivar or management, thus accounting for weather-based potential yield.

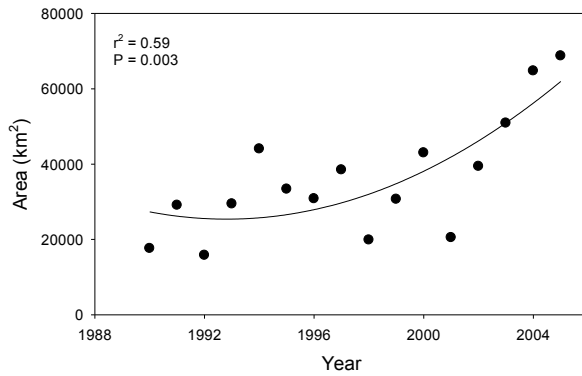


Source: Bell and Fischer (1994).

potential and actual yield averaged 33% for large scale growers and 53% for small scale growers but periods of widening and narrowing gaps were identified in the 22-year

FIGURE 13

Time trend in the area planted to sugarcane in the state of São Paulo, Brazil, where the yield gap was $\leq 20\%$. Yield gap is the difference between actual and water-limited yield.



Source: Marin and Carvalho (2012).

time series of this study; biotic factors such as stem borers possibly contributed to the dynamics of these yield gaps.

Marin and de Carvalho (2012) mapped the gap between actual and water-limited yield of sugar cane in the state of São Paulo (Brazil) and reported a reduction in the gap from 58% in 1990/91 to 42% in 2005/06. The planted area where the yield gap was 20% or less increased markedly after the 2000s (Figure 13). Deployment of improved management underlying the narrowing of this gap was partially associated with higher gasoline-to-ethanol price ratio since the beginning of the 2000s and the availability of biofuel vehicles in Brazil after 2002.

In contrast to the narrowing of yield gaps whereby improved technology over-rides potentially negative factors such as increasing insect pressure, Tiftonell and Giller (2013) present an example of increasing yield gap between fertilised and unfertilised maize in association with depletion of soil nutrients over a 10-year time series in Ivory Coast. Continuous cropping without sufficient input of nutrients and organic matter may lead to significant soil degradation and increasing yield gaps with both technological (i.e. lack of response to improved varieties) and social (i.e. chronic poverty) consequences.

In all the cases outlined in this Section, a dynamic perspective exposes a significant dimension of yield gap.

3.3. MODELLED YIELD

Credible assessment of the impact of technology, soils, current and future climate on food production depends on our ability to estimate crop yields accurately in response to these sources of variation. Crop simulation models, validated on their ability to reproduce major interactions between genotype, environment and management, can help estimate potential and water-limited yields. Here we outline desirable features of models to use in yield gap analysis, and look critically at bias in modelled yield associated with the source of weather data.

3.3.1. Desirable attributes of models in yield gap studies

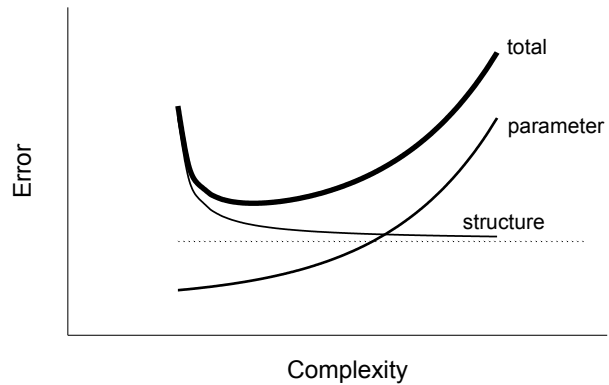
Van Ittersum *et al.* (2013) summarised desirable attributes for models to be used in yield gap analysis. These include use of daily time step weather data, capacity to capture management practices that influence yield (e.g. sowing date, plant density, cultivar maturity), eco-physiological in structure, crop specificity, low requirement of cultivar-specific parameters, proved performance through validation and peer-reviewed publications, full documentation of parameterisation, and user friendly interface. The study of Rötter *et al.* (2012) further highlights the importance of local model calibration.

Crop simulation models estimate different yield levels, depending on the assumptions and modelling approach. Crop models with typically daily time-step and

sufficient detail of physiological principles can be used to estimate yield potential. This involves the assumptions of non-limiting water and nitrogen. Estimates using actual weather, and consequently a certain frequency and intensity of water stress, could be considered closer to water-limited yield. Indeed, modelled yield often reproduces the upper boundary of measured yield under water limiting conditions (Angus & van Herwaarden 2001). Models such as CERES, APSIM, CropSyst, ORYZA2000 and AquaCrop are suitable for estimating both yield potential and water-limited yield (Bouman *et al.* 2001; Jones *et al.* 2003; Keating *et al.* 2003; Stöckle *et al.* 2003; Steduto *et al.* 2009).

FIGURE 14

With increasing model complexity, parameter error increases and structure error decreases towards a limit of irreducible error (dotted line).



Source: Passioura (1996).

There are two trade-offs to consider in selecting modelling methods. First, there is a trade-off between error due to structure and error due to parameters represented in Figure 14. In general, errors associated with structure are reduced when the realism, hence the complexity, of the models increase. The downside of increasing model complexity is a larger number of parameters to be quantified, with the consequent increase in error due to parameters. Second, there is a trade-off between the convenience and likelihood of model adoption and the requirements of data to parameterise and apply models.

3.3.2. Weather data for modelling crop yield

The models commonly used to simulate potential and water-limited yield require a minimum data set of daily weather variables including incident solar radiation, maximum and minimum temperature, precipitation, and some measure of humidity, i.e. relative humidity, actual vapour pressure, dew point temperature. If measured solar radiation is not available (which is often the case), then simulations can be based on the NASA agroclimatology solar radiation data, except at sites with complex topography (Bai *et al.* 2010) or atmospheric pollution (Stanhill and Cohen 2001).

More than 30 weather data sources have been used in agricultural research, but few have been used for simulating yields (Ramirez-Villegas and Challinor 2012). The main differences among sources of the weather databases used to simulate potential and water-limited yields are: (i) observed site-specific vs. interpolated gridded data, (ii) temporal resolution (daily vs. monthly), and (iii) spatial resolution (among gridded databases) (Table 1). Gridded weather data are uniformly distributed within each spatial cell. Values within cells are typically derived by interpolating weather data based on coordinates of the sites within the grid and in nearest-neighbour grids, taking in consideration distance from each other, elevation, and other variables. Gridded weather data have the advantage of full geospatial coverage, but they are derived, not observed data. Various authors have demonstrated that interpolated monthly observations may lead to over-estimation of simulated yields in particular in locations with high day-to-day variability in weather (Soltani and Hoogenboom 2007; van Bussel *et al.* 2011); interpolation of monthly precipitation data in particular leads to substantial error and should therefore be avoided in all cases.

TABLE 1
Classification of global weather databases used to understand current and future agricultural productivity. Weather databases used in the present study have been underlined.

Classification	Source	Time Step	Reference and time interval	Geospatial coverage	Reported variables*	Examples
Point-based data	Weather stations	Daily	HPRCC ^a , CMA ^b , DWD ^c (1983-2010)	Regional	Tmin, Tmax, Precip, Wind speed, Tdew, RH, Vapor Pressure, Radiation	Sinclair & Rawlins. (1993); Grassini <i>et al.</i> (2009)
			NOAA ^d (1900-2010)	Global	Tmin, Tmax, Precip, Tdew, Wind speed, RH, Vapor Pressure	
Gridded data	Interpolated and generated based on data from weather stations, satellites, ocean buoys, etc.	Daily	NCEP/DOE Reanalysis II ^e (1979-2010)	Global (2.5° x 2.5°) (~70,000 km ²)	Tmin, Tmax, Wind speed, Precip, RH, Wind speed, Radiation	Lobell & Asner. (2003); Twine & Kucharik. (2009)
			ERA-Interim Reanalysis (1989-2013) ^f	Global (1.5° x 1.5°) (~25,000 km ²)	Tmin, Tmax, Wind speed, Precip, RH, Wind speed, Radiation	Rötter. (1993); de Wit <i>et al.</i> (2010)
	Interpolated from weather stations	Monthly	CRU05 (3.10) ^g , Univ. Delaware Climate Dataset (1961-2009)	Global (0.5° x 0.5°) (~3,000 km ²)	Tmin, Tmax, Total Precip, number of wet days, Vapor Pressure	Bondeau <i>et al.</i> (2007); Licker <i>et al.</i> (2010)
		Average 50-y monthly mean	WorldClim ^h (1950-2000)	Global (1 km ²)	Tmin, Tmax, Total Precip, number of wet days	Neison <i>et al.</i> (2010); Ortiz <i>et al.</i> , (2008)
	Satellite	Daily	NASA-Power i (1983-2010) except precip (1997-2010)	Global 1° x 1° (~12,000 km ²)	Tmin, Tmax, Precip, Tdew, Radiation, RH	Lobell <i>et al.</i> , (2010)

* Minimum temperature (Tmin), maximum temperature (Tmax), precipitation (precip), dew point temperature (Tdew), relative humidity (RH), incident solar radiation (radiation)

^a High Plains Regional Climate Center (HPRCC). <http://www.cma.gov.cn/english/>

^b China Meteorological Administration (CMA). <http://www.cma.gov.cn/english/>

^c German Weather Service (DWD). <http://www.dwd.de/>

^d National Oceanic and Atmospheric Administration (NOAA): <http://www7.ncdc.noaa.gov/CDO/cdo>

^e National Center for Environmental Prediction/Department of Energy (NCEP). <http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.html>

^f ECMWF re-analysis (ERA): <http://www.ecmwf.int/research/era/do/get/era-interim>

^g Climate Research Unit (CRU). <http://badc.nerc.ac.uk/data/cru/>

^h WorldClim. <http://www.worldclim.org/>

ⁱ National Aeronautics and Space Administration (NASA). <http://power.larc.nasa.gov/>

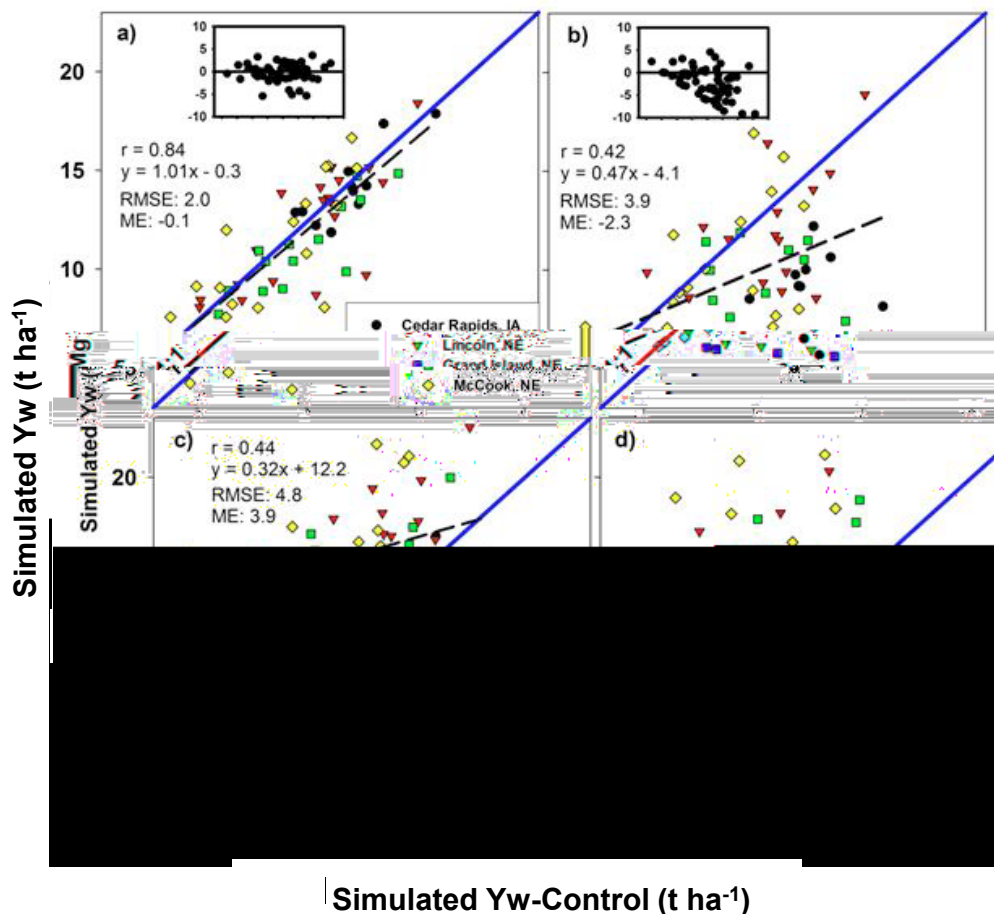
Source: van Wart *et al.* (2013).

Observed daily weather data are unavailable in many cropping regions but gridded global weather databases with complete terrestrial coverage are available. These are typically derived from global circulation computer models, interpolated weather station data, or remotely sensed surface data from satellites. Studies that have used gridded weather databases to simulate yield potential and water-limited yield are rarely validated against simulated yields based on actual weather station data from a location within the same grid.

Van Wart *et al.* (2013) compared three gridded weather databases (CRU, NCEP/DOE, and NASA POWER data) for simulation of water-limited maize yields in four loca-

FIGURE 15

Simulated rainfed maize water-limited yield (Y_w) across four sites in the USA Corn using weather data from (a) NOAA weather stations (Tmax, Tmin, precipitation, and humidity) coupled with gridded solar radiation data from NASA-POWER database, (b) gridded NCEP data, (c) gridded CRU data and (d) gridded NASA plotted against simulated Y_w based on high-quality weather data from meteorological stations of the High Plains Regional Climate Center (HPRCC) network.



Insets show deviations of points from 1:1 line. RMSE and ME units are in t ha⁻¹. Average water deficit (in mm, estimated as the difference between sowing-to-maturity total rainfall and reference evapotranspiration), as determined by simulations using control-data, was -42 (Cedar Rapids, IA), -135 (Lincoln, NE), -149 (Grand Island, NE) and -238 (McCook, NE). Table 1 shows detail of weather databases.

Source: van Wart *et al.* (submitted)

tions across the US Corn Belt (Figure 15). Simulations of water-limited yields based on recorded daily data from well-maintained weather stations were taken as controls. Agreement between simulations of water-limited maize yields based on control weather and those based on gridded weather databases was poor with the latter having strong bias and large root mean square error, 32% to 46% of absolute mean yield across locations and years. Of particular note was the average upward bias of about 4.0 t ha⁻¹ estimated by CRU and NASA. Water deficit (estimated as the difference between sowing-to-maturity total rainfall and reference evapotranspiration) and solar radiation had a large influence on discrepancies between simulated water-limited maize yields estimated by global and control weather databases. In contrast, simulated water-limited yield using observed daily weather data from stations in the NOAA database combined with solar radiation from the NASA-POWER database were in better agreement with water-limited yields simulated with control weather data (i.e., little bias and an RMSE of 16% of the absolute mean). These results highlight the likely bias of simulated agricultural productivity under current and future weather conditions in studies relying on gridded global weather databases. In contrast, point-based simulations of potential and water-limited yields, complemented with an appropriate up-scaling method, perhaps based on agro-ecological zones schemes, may be a more robust approach to achieve full terrestrial coverage without losing accuracy on the estimates of yield potential and water-limited yields (van Ittersum *et al.* 2013).

3.3.3. Modelling yield within the context of a cropping system

For a given region, potential and water-limited yield can be simulated for recommended sowing dates, planting density and cultivar (which determines growing period to maturity). However, sowing dates and cultivar maturity need to reflect the dominant cropping system. The cropping system “context” is critically important in dictating feasible growth duration, particularly in tropical and sub-tropical environments where two or even three crops are produced each year on the same land. Farmers attempt to maximise output of their entire cropping system rather than the yield or profit of individual crops. Likewise, where machinery and labour are limiting or costly, achieving recommended sowing dates may not be feasible for the entire farm. Hence, capturing the spread of sowing dates and of season length is relevant to calculate potential yield or water-limited yield. In all cases, the assumptions must be transparent and consistent with the objectives for proper interpretation of results.

In this way, Grassini *et al.* (2011) simulated an average yield potential of 15.4 t ha⁻¹ for irrigated maize in south-central Nebraska (USA) using current average farmer management practices. However, simulations indicated that use of longer maturity hybrids and higher plant populations could increase average potential yield but trade-offs limited their adoption by farmers, at least under current grain to input price ratios. Trade-offs associated with longer maturity hybrids include higher risk of frost before physiological maturity, difficulties in harvest operations due to wet weather and snow, and grain drying costs. Likewise, yield and economic benefits from higher plant populations can be reduced, or even eliminated, as a result of higher seed costs, higher plant-to-plant variability if intra-row spacing is not uniform and greater incidence of lodging and green snap. Therefore, simulated yield potential based on current dominant management practices may be a more meaningful benchmark for farmers dealing with the trade-off between maximising net return and minimising risk.

4. Approaches to benchmark yield and quantify yield gaps

Analysis of gaps between yield levels allows for identification of constraints, trade-offs and opportunities for improvement. The exploitable yield gap has the greatest practical interest in the context of improving agricultural production. In this Section, we outline the main types of methods used in yield benchmarking and gap analysis using selected case studies. The methods span a broad range of scales, complexities, input requirements and associated errors. We grouped methods in four broad approaches.

Approach 1 compares actual yields with maximum yields measured in high-yielding farmer's fields, experimental stations, or growers contests. Comparisons of this type are spatially constrained by definition, and are an approximation to the gap between actual and attainable yield. This approach can be biased, however, where best management practices are not feasible; in these cases modelled yields provide more relevant benchmarks. *Approach 2* is based on comparisons of actual yield, but instead of a single yield benchmark, yield is expressed as a function of one or few environmental drivers in simple models, usually using boundary functions as reference. In common with Approach 1, these methods do not necessarily capture best management practices. *Approach 3* is based on modelling which may range from simple climatic indices to models of intermediate (e.g. AquaCrop) or high complexity (e.g. CERES). *Approach 4* involves a range of methods combining remote sensing, actual data, GIS, and models of varying complexity. This approach is mostly used at and above the regional scale.

4.1. APPROACH 1: HIGH-YIELDING FIELDS, EXPERIMENTAL STATIONS AND GROWERS CONTESTS

Yields in farmer's fields can be benchmarked against various references, including the best performing crops in neighbouring fields, yield in experimental stations or yields in growers contests where similar soil, topography, weather, and biotic conditions apply.

4.1.1. Sunflower in rainfed systems of Argentina

Hall *et al.* (2013) benchmarked yield of rainfed sunflower at the regional to national level in Argentina. The 2.25 Mha sunflower-growing area was categorised, on the basis of expert opinions, into eight regions. Within each region, reported yields for those districts contributing most to total regional yield were used to estimate mean actual yield on a yearly basis. Mean yields from comparative yield trials were used as an estimate of attainable yields for each year and region combination. These attainable yields approximate water-limited yields (Section 2.2). Years of suitable data varied across regions from 5 to 9. The actual/attainable yield gap was significant in all regions, and ranged between 20 and 77 % of mean actual yields, which – in turn – ranged from 1.52 to 2.25 t ha⁻¹ across regions. At a whole-country level, the mean actual/attainable yield gap was 0.75 t ha⁻¹, equivalent to 41 % of mean country yield of 1.85 t ha⁻¹.

For five of the eight regions, yield data for individual fields were also available. Mean individual field yields in these regions were significantly lower than attainable yield estimates derived from comparative yield trials, but the mean values for

the top deciles of commercial fields (an alternative estimate of attainable yield) were indistinguishable (three regions) or slightly greater (two regions) than the estimates of attainable yield derived from comparative yield trial estimates. A third estimate of mean regional attainable yield, the 95th percentile of ranked reporting district yields pooled across years and reporting districts within each region, was also calculated. These estimates, which importantly do not allow calculation of yearly values of the actual/attainable yield gaps, underestimated mean attainable yields derived from comparative yield trials in four out of eight regions and attainable yields derived from individual fields in all five regions for which this data was available. These contrasts between estimates of attainable yield are useful as indicators of strengths and weakness of the three approaches.

An important additional message arising from the whole analysis, and which bears on the use of model-derived estimates of attainable yield, was the overriding importance of spatial and inter-annual variation in environmental (including management) conditions on yield. This was evident in the databases for reporting districts, for comparative yield trials, and for individual commercial fields. More effort is needed to understand the causes of this variability and, especially, on the effects of spatial scale on the values of actual/attainable yield gap estimates.

4.1.2. Maize in sub-Saharan Africa

Sileshi *et al.* (2010) compared actual maize yield obtained with inorganic and organic nutrient inputs with control (no input) on experimental stations and farm fields. The comparison also involved yield gaps with inorganic and organic fertilisers, i.e. *in situ* green manure from sunhemp (*Crotalaria* spp.), velvetbean (*Mucuna* spp.), sesbania (*Sesbania* spp.), tephrosia (*Tephrosia* spp.) and gliricidia (*Gliricidia sepium*) on different site conditions. For each input tested at a given site or in a particular season, there was a corresponding grain yield from maize grown continuously without external nutrient input (control) thus constituting a pair of means (treatment and control). The number of countries covered, number studies, pairs of means extracted and robust parameter estimates of yield gaps for each treatment are summarised in Table 2. This analysis did not apply the hierarchy of yields commonly used for gap analysis (Section 2.2); instead, an *ad hoc* gap was defined as the difference in grain yield between maize grown using a given nutrient input and the control under a specific study condition.

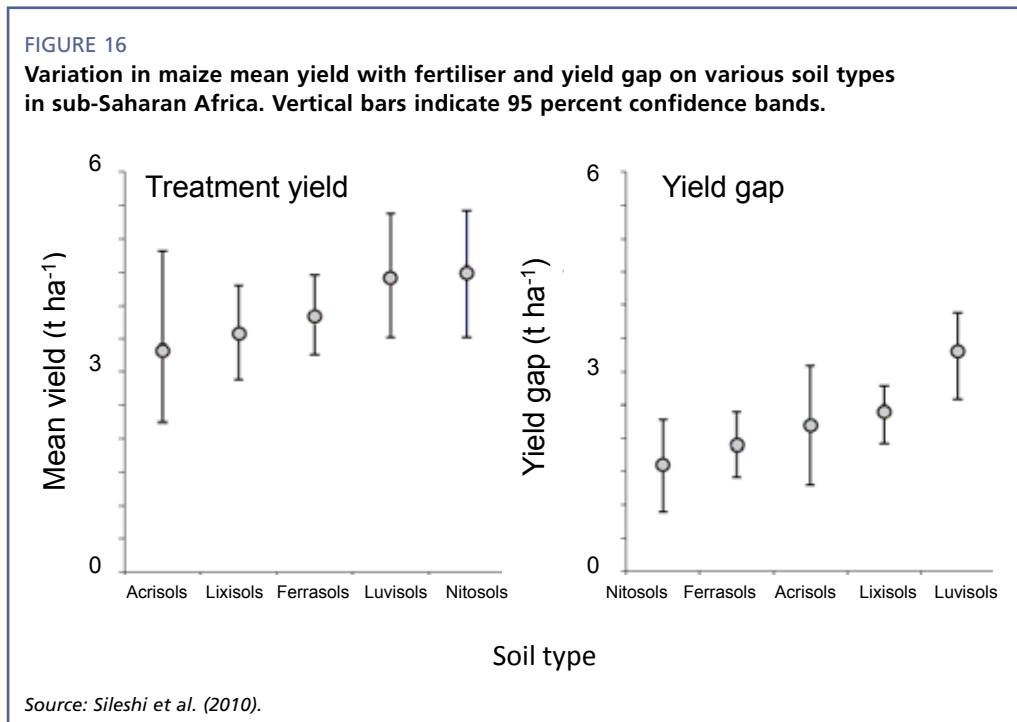
TABLE 2
Basic statistics and robust parameter estimates (Winsorized means and coefficients of variation) of maize grain yield (t ha⁻¹) from various soil fertility management inputs.

	Control	Fertiliser	Sunhemp	Velvetbean	Sesbania	Tephrosia	Gliricidia
Number of countries	12	13	11	12	7	9	5
Number of studies	110	71	39	45	42	28	14
Pairs of means [#]	473	346	214	242	262	177	114
Estimated mean	1.4	3.9	3.3	2.8	2.9	2.0	3.3
95% confidence band	1.3-1.4	3.7-4.1	3.0-3.6	2.6-3.1	2.6-3.1	1.6-2.2	3.0-3.6
CV (%)	69.3	46.3	54.4	59.4	67.2	67.3	43.0

[#] Total number of pairs of means (treatment and control) from all published studies.

Most studies reported means from more than one season and site, and more than one treatment with the same control.

Source: Sileshi *et al.* (2010).



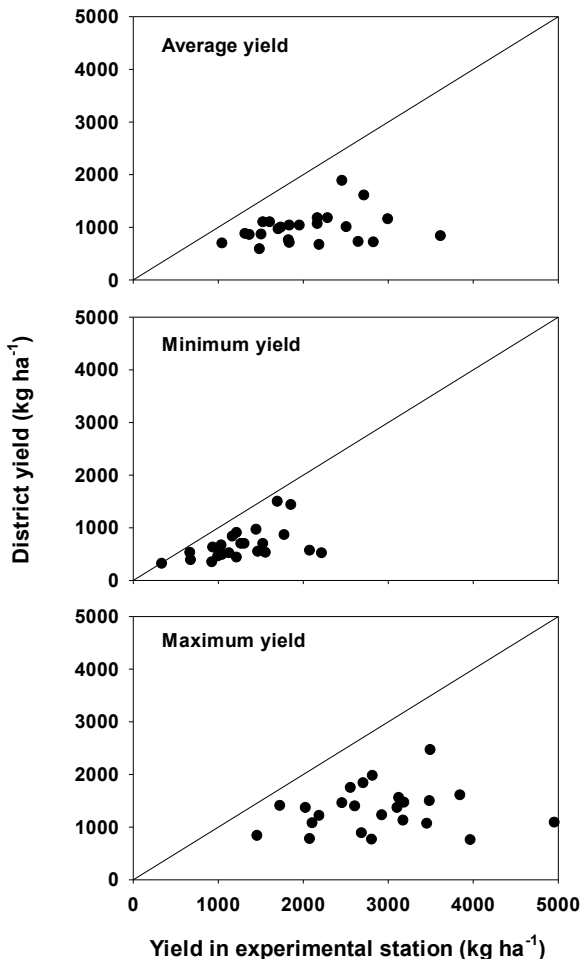
Despite the genetic potential of maize to yield up to 10 t ha⁻¹, actual yields did not exceed 8 t ha⁻¹ in the majority of cases. The probability of exceeding 8 t ha⁻¹ was <3% with the recommended rate of fertiliser, while in 75% of the cases yields were <5 t ha⁻¹ with all inputs. Inorganic fertiliser increased yield and reduced the coefficient of variation relative to both the unfertilised control and organic nitrogen treatments. Yield gains were however lower and more variable on farmers' fields than in research stations. These differences may be caused by factors that are generally not transferable, such as environmental conditions and management practices on research stations where stricter attention is paid to sowing dates, spacing, weeding, fertiliser doses and pest control than in farmers' fields.

Refined statistical analyses also suggested variation in yield gaps with elevation, mean annual precipitation and soil type, including clay content. Although yields with the recommended rate of inorganic fertiliser were generally higher on Nitosols than other soil types, yield gains over the control were the lowest (Figure 16). The lower gain on Nitosols could be explained by the 'saturated soil fertility' effect. Variability in yield gaps (indicated by the 95% confidence bands) was highest on Acrisols and Nitosols and lowest on Lixisols. The high variability on Acrisols could be attributed to their sensitivity to degradation (Stocking, 2003). Overall, the analyses indicated that organic inputs from the legumes may have large impacts on more sensitive and less resilient soils.

Variation in yield gaps with elevation, mean annual precipitation and the clay content of the soil were also significant in some cases. For example, for maize grown with inorganic fertiliser, the partial predictions of yield gap had a strong quadratic relationship with elevation and soil clay content. The 95% confidence bands also indicated negative values on sites with elevations below 600 m or above 1300 m, and soil clay content below 20% or above 40%. The 95% confidence bands also widened, indicating increasing risks of using inorganic fertiliser outside this range. Similarly, soil clay content significantly influenced yield gaps in the treatments that receive organic nitrogen from sunhemp, sesbania and tephrosia.

FIGURE 17

Comparison of average, minimum and maximum yield of peanuts measured in experimental stations and in whole-districts of India. The lines are $y = x$.



Source: Bathia *et al.* (2006).

Yield gaps also varied with overall site productivity indicated by the control yield. Yield gains with inorganic fertiliser were as high as 8 t ha^{-1} where the control achieved $<2 \text{ t ha}^{-1}$, while they remained below 4 t ha^{-1} where the control achieved more than 2 t ha^{-1} .

4.1.3. Grain legumes in India

Bathia *et al.* (2006) analysed regional-level yield gaps of soybean, peanut, chickpea and pigeonpea in India. They compared actual yield in experimental stations, best farms, and whole-districts. An interesting aspect of this work is that mean, maximum and minimum yields were derived for each yield category and used for yield gap calculations (Figure 17). The information from each of these measures of yield gap is different, and the distinction is particularly important when identifying the putative causes of the gaps. Nutrient supply for example is a much more likely cause of gaps in maximum yield, i.e. the yield achieved in more favourable (wetter) seasons than in causing gaps when yield is small. Efforts to identify specific yield gaps in extreme seasons are important for risk management, and to allow for the capture of the benefits of better seasons.

4.1.4. Wheat-maize double crop in the Hebei plain of China

Most benchmarking studies focus on single crops. Liang *et al.* (2011) is one of few exam-

ples targeting double crops. The study was based on a survey of 362 farms in six counties of the Hebei Plain, where wheat–maize double crop is the most important component of the system. Survey data from a single season were used to calculate maximum, average and minimum yield. These yields were compared with (a) modelled yield, and (b) experimental yield in growers' fields during the same season; trials were designed and managed by researchers using recommended practices seeking high yield. The authors of the study defined modelled yield as the "climate-driven potential", which corresponds to the definitions of Y_p or Y_w depending on water supply (Section 2.2).

Best farmer yield of wheat, maize and aggregated wheat-maize was close to the experimental yield, and about 78–89% of potential yield estimated with models (Figure 18), suggesting that there is no residual exploitable gap for the best farmers. The gap between average and best yield was around 30% for both individual crops and whole-system. Based on interviews and field observations, Liang *et al.* (2011) identified agronomic and socio-economic issues underlying yield gaps. For example, lack of access to shared irrigation facilities precludes the adoption of wheat irrigation at stem elongation, as recommended.

4.2. APPROACH 2: BOUNDARY FUNCTIONS ACCOUNTING FOR RESOURCES AND CONSTRAINTS

Crop yield is a function of capture and efficiency in the use of resources, and non-resource constraints modulating crop development, morphology, and physiology (Figure 19). To account for both resources and non-resource environmental factors, methods have been developed that are based on the notion of boundary functions (Box 3). Boundary functions have been used to benchmark yield in relation to resources, mostly water (Section 4.2.1) and nitrogen (Section 4.2.2), and soil constraints (Section 4.2.3).

4.2.1. Yield and water productivity gaps

This approach was pioneered by French and Schultz (1984a, 1984b) for rainfed wheat in Australia and has been more recently applied to a range of rainfed and irrigated cropping systems worldwide. The method can be applied to water use during the whole season, or limited to crop-specific critical periods.

4.2.1.1. Wheat in rainfed systems

French and Schultz (1984a, 1984b) benchmarked wheat yield in south-eastern Australia, and identified management and environmental causes of the gap between actual and attainable yield. Here we outline the concept and update the benchmarking of wheat in dryland systems.

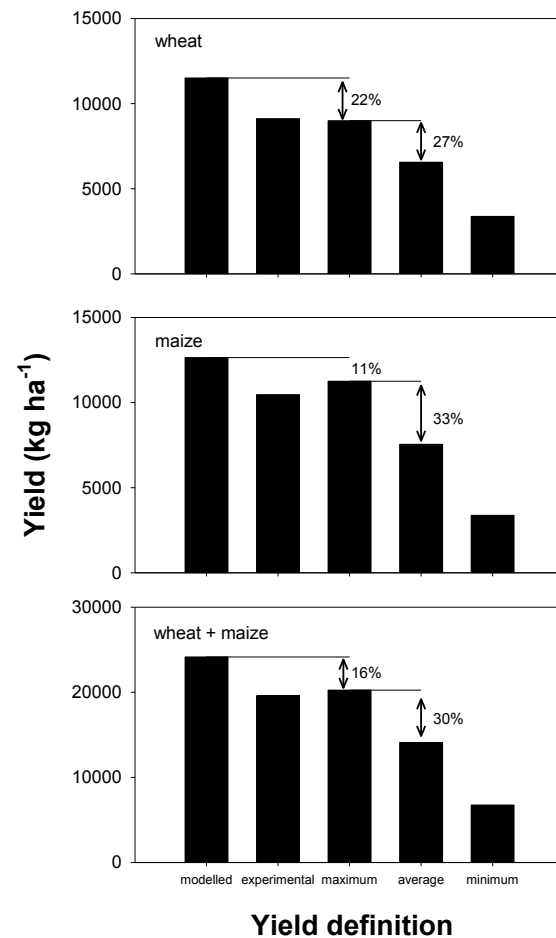
These authors plotted grain yield against evapotranspiration (ET) of wheat crops, estimated as soil water at sowing plus in-season rainfall, in diverse locations and seasons, and fitted a boundary line with biophysically relevant parameters (Figure 20a):

$$Y_w = TE_Y * (ET - E)$$

Where Y_w is water-limited yield, the slope TE_Y can be interpreted as the maximum transpiration efficiency for the production of grain, and the x-intercept E can be interpreted as non-productive water loss, primarily soil evaporation. The characteristic slope in the original study was $20 \text{ kg grain ha}^{-1} \text{ mm}^{-1}$, and was supported by physiological considerations. The authors recognised the x-intercept was dependent on environmental conditions, chiefly rainfall and soil, and suggested a range between 30 and 170 mm for crops in eastern Australia. For instance, 30 mm would be more typical of northern regions where water supply involves a large proportion of stored soil moisture and relatively few, normally large rainfall events during the season. In southern

FIGURE 18

Yield gap analysis of wheat-maize double cropping and its components in the Hebei plain of China. Yields are potential, calculated with models; experimental, measured in researcher-designed trials in growers' fields, and maximum, average and minimum yield from surveys.



Source: Liang et al. (2011).

BOX 3

BOUNDARY FUNCTIONS

Yield gaps result because one or more factors (for example water and nutrient availability) limit crop yield. This limiting effect in biophysical systems can sometimes be estimated using boundary functions, first proposed by Webb (1972). While evaluating fruit size in strawberry, he discovered that berry weight, when plotted against achene number, always lay below or near a linearly increasing boundary. He proposed that the boundary represented the limiting effect of achene number on strawberry weight, and that the measurements lying below the boundary were limited by other factors, for example water deficit. Since that time the boundary line has become a popular model for limiting responses in biological data, including several examples on crop yield (Casanova *et al.* 1999; French and Shultz 1984).

Most methods for fitting boundary lines have been somewhat *ad-hoc*. In some cases a line is simply drawn by eye. Other methods rely on using an arbitrarily chosen threshold to select a subset of the data to which the boundary line is fitted using the least squares method (Webb, 1972). In some cases, the parameters of the boundary function are derived from physiological or agronomic principles (Section 4.2.1.1).

These methods have been subject to criticism because they lack an underlying statistical model. A second criticism is that boundary lines are often used inappropriately. For example in cases where the boundary line model does not make biological sense (i.e. when we would not expect the independent variable to limit the dependent variable) or where there are simply insufficient data in the neighbourhood of the boundary to estimate its location (i.e. when there are too few data or when other more limiting factors are prevalent). Milne *et al.* (2006a, 2006b) addressed these issues by proposing (i) an objective method of fitting boundaries, and (ii) methods for assessing whether the models are appropriate for given sets of data.

The method of Milne *et al.* (2006a) assumes that the data follow a censored bivariate normal distribution, where the boundary line defines the censor. Maximum likelihood is used to estimate the distribution parameters. Unlike many other methods of fitting a boundary line all of the data points are used, not just an arbitrarily selected subset. The parameters for the censored distribution comprise those which describe the bivariate normal part of the model, the parameters of the boundary line (e.g. for a straight line boundary $y = ax + b$ these are a and b); and a parameter which describes the variation around the boundary (σ_B). The latter is attributed to measurement error, and so σ_B , provides an indication of how certain we are of the position of the boundary line. Confidence intervals for the parameter estimates are calculated from the Fisher information matrix (Milne *et al.* 2006a). The equation of the boundary line (e.g. straight line, parabola etc) is defined in the statistical model prior to fitting the parameters. Visual inspection of the data and knowledge of the biological system help decide which form of boundary line should be used. To assess the suitability of the boundary line model (i.e. the censored distribution) to describe the data, the analyst can compare its performance with a bivariate normal distribution (Milne *et al.* 2006a). The latter model is the null hypothesis against which the evidence for the boundary is assessed. The model with the censor has more parameters than the one without. Typically goodness of fit improves with increasing number of parameters. To account for this association, we compare the models using Akaike's information criterion (AIC) (1973) which measures performance based on a compromise between parsimony and goodness of fit.

The AIC is given by

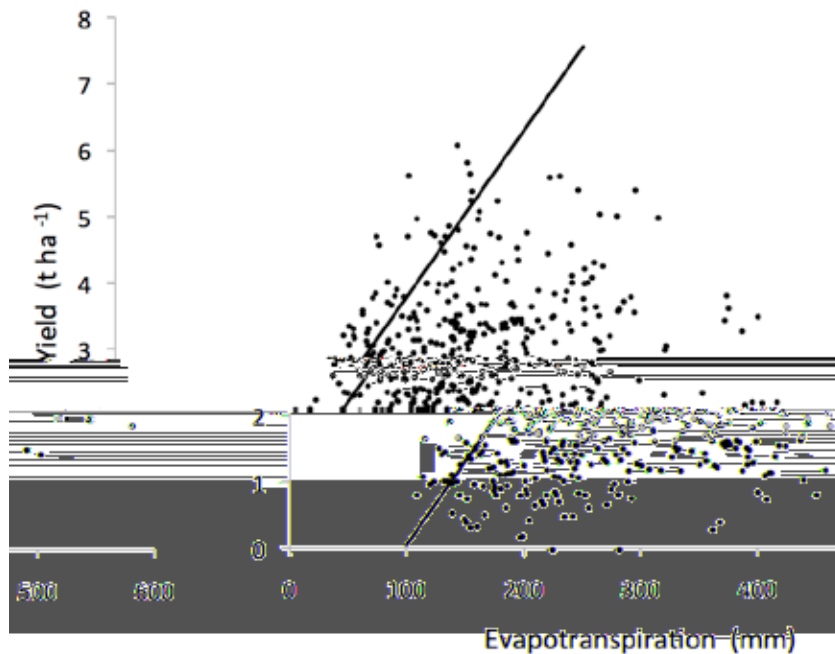
$$\text{AIC} = -2\ln M + 2p$$

where M is the maximum likelihood value and p is the number of parameters in the model. The smaller the AIC value the more appropriate the model.

Figure Box 3-1 shows an example of a boundary line model fitted to data relating evapotranspiration and yield of wheat crops in dry environments worldwide. With no previous assumptions, except for the linearity of the model, and using the whole data set, Milne *et al.* (2006a) method returned a slope = 24.6 kg ha⁻¹ mm⁻¹, with 95 percent confidence interval (-3.412, -1.504). This compares with the 22 kg ha⁻¹ mm⁻¹ rate based on a combination of empirical line fitting informed by physiological principles (Section 4.2.1.1).

FIGURE BOX 3-1.

Example of linear boundary function fitted with the method of Milne *et al.* (2006a, 2006b). Data are actual wheat yield vs estimated evapotranspiration in China, the Mediterranean region of Europe, North America and Australia compiled by Sadras and Angus (2006). A boundary line of the form $y = ax + b$ was assumed. The estimated parameter values were $a = 0.025$ with 95 percent confidence interval (0.020, 0.030) and $b = -2.458$ with 95 percent confidence interval (-3.412, -1.504). The variation around the boundary, $\sigma_B = 0.971$, with confidence interval (0.791, 1.151). According to the AIC the boundary line model describes this data better than a bivariate normal model.



regions where initial soil water is generally low, and crops rely on winter rainfall, the combination of small rainfall events and hard setting soils with poor infiltration, surface ponding and run-off could lead to x-intercepts about 170 mm.

As with any empirical model, the parameters need local calibration, and extrapolation beyond the range of tested applicability should be avoided. For example, the slope representing attainable yield per unit transpiration is expected to be larger

FIGURE 19

Crop growth and yield depend on the capture and efficiency in the use of resources (CO_2 , radiation, water and nutrients) and environmental factors modulating the development, morphology and physiology of the crop.

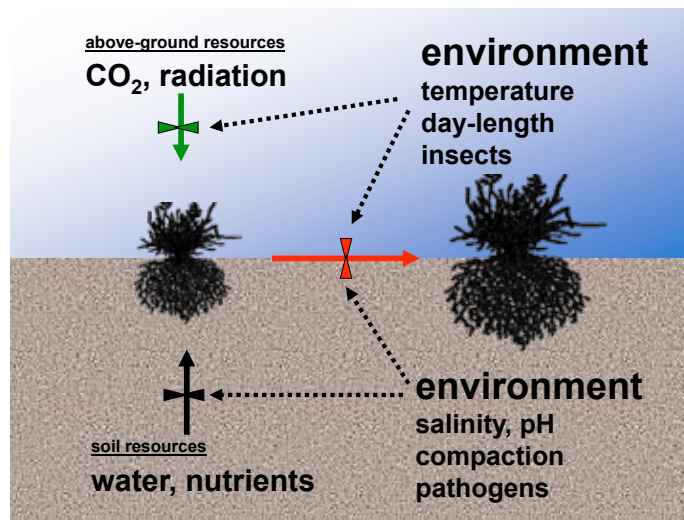
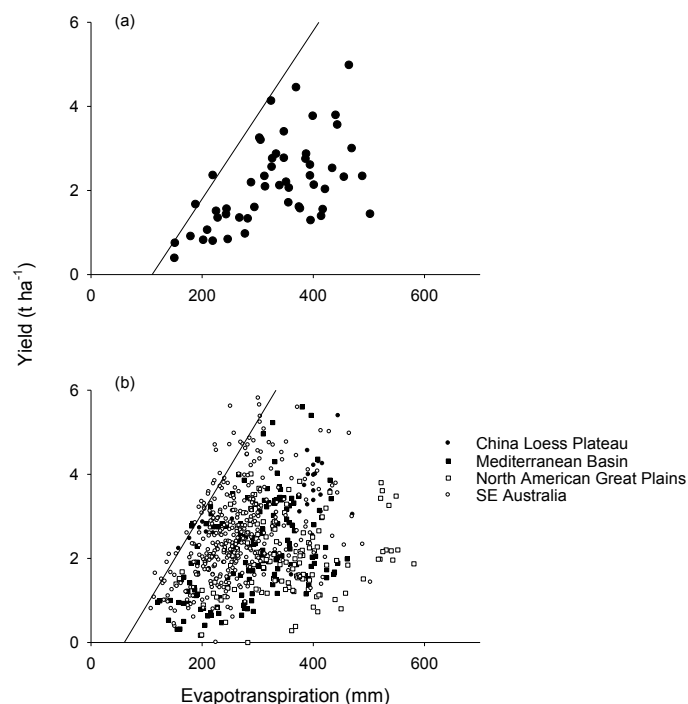


FIGURE 20

(a) The original model of French and Schultz (1984) assumed a boundary function with slope = $20 \text{ kg grain ha}^{-1} \text{ mm}^{-1}$ and x-intercept = 110 mm (solid line) for a particular set of crops comprising South Australian environments and cultivars and management of the 1960-70s (circles). (b) The original concept, with an updated slope = $22 \text{ kg grain ha}^{-1} \text{ mm}^{-1}$ and x-intercept = 60 mm , applied to a large ($n=691$) data set of crops in four dry environments of the world.



Source: Sadras and Angus 2006.

under conditions that favour high biomass per unit transpiration and high harvest index, namely low vapour pressure deficit, high proportion of diffuse radiation, high radiation-to-temperature ratio, high atmospheric concentration of CO_2 , and a high proportion of water available around and after flowering (Abbate *et al* 2004; Rodriguez and Sadras 2007; Sadras and Rodriguez 2007).

The main environmental sources of variation in the x-intercept are soil characteristics (French and Schultz 1984a,b; Ritchie 1972) and the seasonality and size structure of rainfall, i.e. the x-intercept is smaller for crops grown with high stored water/seasonal rain ratio, and with dominance of large rainfall events during the growing season (Sadras and Rodriguez 2007a). Other factors that affect seasonal soil evaporation, chiefly by changing the partitioning of radiant energy between canopy and soil, include tillage and stubble management, row-spacing and sowing density, the rate of canopy expansion early in the season and the rate of senescence as affected by cultivar and management (Cooper *et al.* 1987; Monzon *et al.* 2006; Richards 2006).

Four elements reinforce the notion that the model of French and Schultz is robust and agronomically relevant to benchmark yield of rainfed wheat. First, a line with slope = $22 \text{ kg grain ha}^{-1} \text{ mm}^{-1}$ and x-intercept = 60 mm provided a reasonable upper boundary for a large number of crops from diverse regions of the world (Figure 20b). Second, the simpler boundary function of French and Schultz generally agrees with boundary functions generated with more complex simulation models involving dozens of parameters and daily

input of weather variables (O’Leary and Connor 1996; Angus and van Herwaarden 2001; Asseng *et al.* 2001; Sadras and Rodriguez 2007; Hochman *et al.* 2009). In fact, the French and Schultz model is often considered a back-of-the-envelope check for more refined models. Third, a close alignment between actual yield-to-transpiration ratios corresponding to 150 years of wheat breeding in Australia, and the original (20 kg grain ha⁻¹ mm⁻¹) and current (24 kg grain ha⁻¹ mm⁻¹) estimates of the model’s slope reinforce our confidence in both the value and interpretation of this parameter (Sadras and Lawson 2013a). Fourth, the method of Milne *et al.* (2006a; 2006b) applied to the data set in Figure 20b returned parameters that, without *a priori* assumptions, is consistent with the parameters in the model of French and Schultz (Box 3).

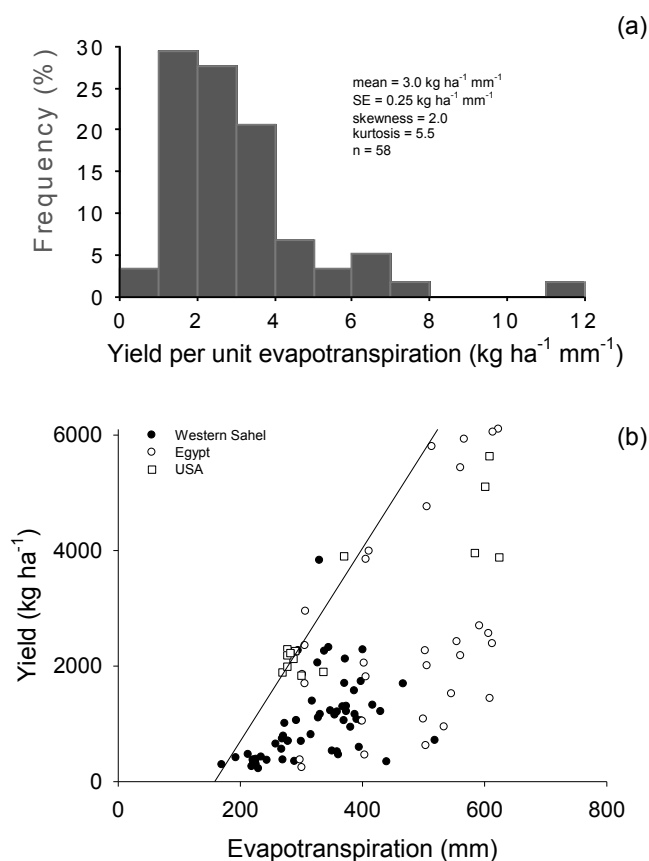
In summary, the approach of French and Schulz is solid, despite the lack of consideration of seasonal dynamics of rainfall and water use. This method is attractive for its simplicity, and results in estimates that are not necessarily worse than those derived from more complex, daily-time step crop models, provided the parameters are adjusted to local conditions. Of the two parameters, the slope can be considered robust and taken as crop-specific constant in a first approach, whereas care should be taken to derive sensible values for the x-intercept. The approach of French and Schultz has been limited to Australia until recently, but tests in other regions of the world and crops suggest a broader generality (Sections 4.2.1.2 to 4.2.1.4). This approach is useful to benchmark attainable yield against water use, with relatively low demand of inputs, namely estimates of initial and final soil content and in-season rainfall to estimate evapotranspiration, and measured yield. French and Shultz-type boundary functions can also be derived using models like CropSyst, CERES or APSIM, or a combination of actual data and modelling, e.g. actual yield and modelled evapotranspiration.

4.2.1.2. Millet in low-input systems of Africa

Sadras *et al.* (2012) compiled millet grain yield and water-use data from published sources, mostly from the West African Sahel generally associated with ICRISAT. Data from Egypt, a more favourable African environment, and the United States, to represent higher-input cropping systems, were included in the analysis for comparison. For a collection of 58 crops in the Sahel, millet yield per unit water use averaged 3 kg grain ha⁻¹ mm⁻¹ (Figure 21a). Yield per unit transpiration of millet is the lowest among C4 crops and is primarily associated with low harvest

FIGURE 21

(a) Frequency distribution of millet yield per unit seasonal evapotranspiration in Western Sahel and (b) relationship between grain yield and evapotranspiration for crops in Western Sahel; data from Egypt and USA are included for comparison. The solid line has a slope = 16.7 kg grain ha⁻¹ mm⁻¹ and an x-intercept = 158 mm, both derived from Rockström *et al.* (1998).



Source: Sadras *et al.* (2012).

index. However, millet's low harvest index needs to be considered in the context of a trade-off between grain production and valuable crop residues. For example, some popular landrace millet varieties in India are over 3-m tall, and are valued for the large amount of fodder they provide, even though grain yields are relatively low.

A boundary function with a slope of $16.7 \text{ kg grain ha}^{-1} \text{ mm}^{-1}$ captured the upper limit of water productivity for millet crops (Figure 21b). This boundary function applied to the stressful Sahel conditions, and to the more favourable environments of Egypt and North America. Most millet crops in the Sahel were well below this boundary function. Environmental, management and plant-related factors contributed to the low water productivity of millet in the Sahel. Low soil fertility and sparsely sown crops mean ground cover is typically low, i.e. peak leaf area indices are normally below 1, or below 2 in more intensive systems. This in turn favours unproductive soil evaporation. Sandy soils, which are prone to crusting, favour episodic runoff and deep drainage. Indeed, a series of experimental and modelling studies converge to conclude that production in these environments is less limited by water than by soil fertility, agronomy and inputs, as there is often residual water in the soil at maturity, large unproductive losses of water are common, and nutrient stress is often more severe than water stress (Sadras *et al.* 2012).

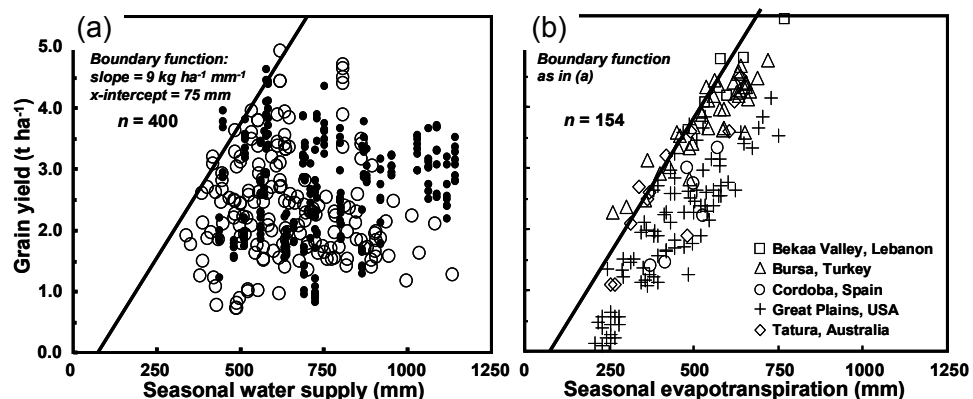
4.2.1.3. Sunflower in rainfed systems of Argentina

Grassini *et al.* (2009a) explored the relationship between sunflower grain yield and seasonal water supply using a 4-year database of commercial crops in the Western Pampas ($n = 169$; paddock size between 21 and 130 ha). Only crops grown on deep soils with no obvious physical or chemical constraints to rooting were included. Data collected from small-plot (56 m^2) fertilization studies were also included in the analysis ($n = 231$). Water productivity for each field-year was calculated as the quotient between grain yield and seasonal water supply, where water supply is initial soil water plus seasonal rainfall.

The boundary function that delimits the maximum yield over the range of water supply had a slope of $9.0 \text{ kg grain ha}^{-1} \text{ mm}^{-1}$ and an x-intercept of 75 mm (Figure 22a). Salient features of this figure are: (i) many crops had water supplies greater than the maximum expected cumulative evapotranspiration (630 mm) for the region, (ii) yield varied widely

FIGURE 22

(a) Relationship between sunflower grain yield and seasonal water supply in farmers' fields (open symbols; $n = 169$) and small-plot fertilizer trials (closed symbols; $n = 231$) in the Western Pampas. Water supply is available soil water at sowing plus sowing-to-maturity rainfall. (b) Relationship between yield and evapotranspiration for sunflower crops in Australia, Lebanon, Spain, Turkey, and United States.



Source: Grassini *et al.* (2009a).

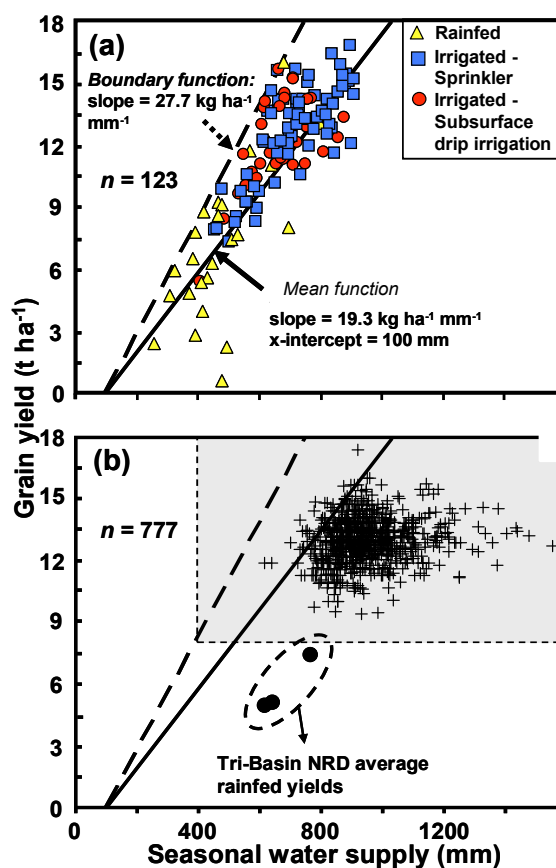
for a given water availability, (iii) on average, farmers' yields were 50 percent below the boundary function, and (iv) maximum on-farm grain yields (4.9 t ha^{-1}) approached those reported for modern hybrids under potential conditions. Average on-farm yield per unit water supply ranged from 1.1 to $8.0 \text{ kg grain ha}^{-1} \text{ mm}^{-1}$. The boundary function defined for the Western Pampas provided a reasonable upper limit for rainfed and irrigated sunflower crops grown in other semi-arid environments in the Mediterranean Basin (Lebanon, Spain, Turkey), the Great Plains of North America and Australia (Figure 22b). Although crops were grown under good management practices, most of the data points were below the boundary function. The gaps were associated with high soil evaporation, high evaporative demand of the atmosphere, and untimely rainfall during the growing cycle in relation to critical crop stages. Splitting crops in three categories depending on the range of water supply allowed for more refined identification of agronomic and environmental factors underlying the yield gaps (Grassini *et al.* 2009a).

4.2.1.4. Maize in irrigated systems of USA

Grassini *et al.* (2009b) compiled data on maize grain yield, applied irrigation, irrigation system and nitrogen fertiliser rate during three years from commercial irrigated fields inside the Tri-Basin Natural Resources Districts of Nebraska, USA ($n=777$; paddock mean size: 46 ha). Seasonal water supply was calculated as available soil water at sowing + sowing-to-maturity rainfall + applied irrigation. Modelled yield and water supply in 18 locations across the Western U.S. Corn Belt were used to derive (i) a boundary function (slope = $27.7 \text{ kg grain ha}^{-1} \text{ mm}^{-1}$, x-intercept = 100 mm) and (ii) a mean function (slope = $19.3 \text{ kg grain ha}^{-1} \text{ mm}^{-1}$, x-intercept = 100 mm). The boundary function defines the maximum yield over the range of water supply, and the mean function accounts for the variability in attainable yield at a given water supply caused by year-to-year variation in solar radiation, temperature, vapour pressure deficit, and seasonal distribution of water supply. When compared to reported data on grain yield and water supply from maize crops in the Western US Corn Belt under good management, both the boundary and mean functions proved to be robust benchmarks (Figure 23a). On average, farmers' yields were 20 percent below the mean benchmark function although ≈ 4 percent of the cases approached or even exceeded this benchmark (Figure 23b). Grain yield was not responsive to water supply over 900 mm; an important fraction of the total fields (55 percent) exceeded the apparent 900 mm threshold required to maximize yield. The apparent water excess

FIGURE 23

a) Relationship between grain yield and seasonal water supply (available soil water at sowing plus sowing-to-maturity rainfall and applied irrigation) for maize crops grown under near-optimal management in the Western US Corn Belt. The database included a wide range of environments and irrigation schedules; none of the fields had obvious nutrient limitations, diseases, insect damage, weeds, or hail. (b) Farmers' irrigated yields in the Tri-Basin NRD as a function of seasonal water supply (+). Tri-Basin county-level average rainfed yields are also shown for comparison (•).



Source: Grassini *et al.* (2011).

was weakly related to available soil water at sowing and sowing-to-maturity rainfall but strongly related to applied irrigation. Water productivity of irrigated crops ranged from 8.2 to 19.4 kg mm⁻¹ ha⁻¹ across field-years. Average water productivity was higher in irrigated than in rainfed crops (14.0 vs 8.8 kg grain ha⁻¹ mm⁻¹).

Fields under centre pivot irrigation had higher water productivity (\approx 13 percent) than their counterparts under gravity irrigation. Yield per unit irrigation averaged 44, 62, and 77 kg grain ha⁻¹ mm⁻¹ under pivot and 28, 36, and 42 kg grain ha⁻¹ mm⁻¹ under gravity in 2005, 2006, and 2007, respectively. When these values were corrected by the average rainfed yield on each year (5.1, 5.2, and 7.5 tonnes ha⁻¹), the resulting water productivity became relatively stable across years: 27, 37, and 32 kg grain ha⁻¹ mm⁻¹ under pivot and 18, 21, and 18 kg grain ha⁻¹ mm⁻¹ under gravity in 2005, 2006, and 2007, respectively. High ΔY per unit irrigation reflects not only the response to increasing water supply, but also differences in the agronomic management between irrigated and rainfed crops (e.g. plant population, nutrient inputs). Consequently, rainfed crops had lower attainable yield and water productivity than irrigated crops (Figure 23b).

4.2.1.5. Yield vs water availability in a critical period of yield determination

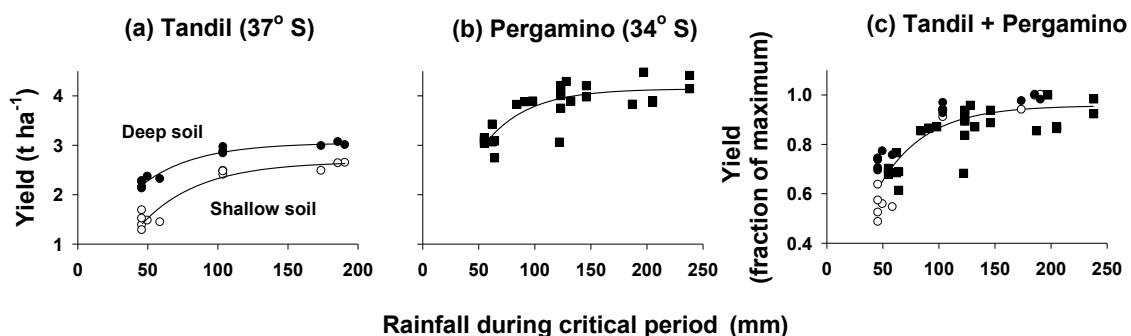
Calviño and Sadras (1999) benchmarked soybean yield in the Pampas of Argentina, in a period of fast change and adoption of technology including the first generation of transgenic (herbicide tolerant) varieties. Their aim was to produce a reference to measure the impact of changing technology, including new varieties and management practices, and to identify causes of gaps between actual and attainable yield. They gathered yield and rainfall data from 30–35 crops per year in farmers' fields during four years. The period was long enough to span an important range of rainfall, and short enough to meet the assumption of constant technology. To reinforce this assumption, additional criteria were used to narrow the range of crops in the sample, e.g. fixed row spacing, narrow sowing date window, narrow range of maturity groups. Using the 3-highest yielding crops each season as a measure of water-limited yield, they fitted the boundary model (Figure 24):

$$Y_w = a + b (1 - e^{-c W})$$

where a , b and c are empirical parameters, and W is rainfall in February plus a carry-over of January rainfall; a estimates yield when $W = 0$, and $a + b$ is the maximum

FIGURE 24

Relationship between attainable soybean yield and rainfall during the period of pod and grain set in (a) deep and shallow soils at Tandil, (b) deep soil at Pergamino, (c) combined data for Tandil and Pergamino. Curves are: (a) deep soil, $y = 0.25 + 2.79 (1 - e^{-0.0258 x})$; shallow soil, $y = -1.15 + 3.81 (1 - e^{-0.0240 x})$; (b) $y = -0.56 + 4.7 (1 - e^{-0.0259 x})$, (c) $y = -0.059 + 1.02 (1 - e^{-0.0242 x})$.



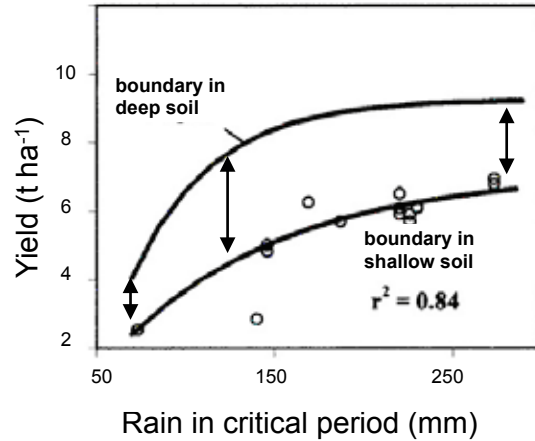
Source: Calviño and Sadras (1999).

attainable yield. Similar to the model of French and Schulz, this model establishes a boundary function in relation to water availability. In contrast to the model of French and Schulz, the parameters of this model cannot be explained in terms of biophysical processes except for the estimate of attainable yield. Also unlike the model of French and Schulz, this model captures the physiological principle of a most critical period for yield determination (Andrade *et al.* 2005), i.e. instead of using seasonal water use, it constrains the driving variable to the typical window of pod and grain set in February.

A similar approach was used by Calviño *et al.* (2003) to benchmark maize yield in the Pampas. They collected yield data from 216 commercial crops in Tandil (37 °S, 59 °W) from three-year time series to meet the criterion of constant technology, reinforced with specific criteria to narrow the range of agronomic practices. A boundary function was fit that related the yield of the 15% highest yielding crops and rainfall from 30 d before to 20 d after flowering, the critical period for grain yield determination in maize. The boundary function was tested against independent data, and was used to estimate the yield gap associated with shallow soils (Figure 25). The double-headed arrows in Figure 25 highlight that the yield gap between shallow and deep soils is smaller under both low and high rainfall conditions, when the storage capacity of soil is less relevant; the largest gap is at intermediate rainfalls when storage capacity of soil water buffers dry spells between rainfall events.

FIGURE 25

Attainable yield of maize as a function of rainfall in the critical period of grain yield determination for deep Typic Argiudolls and shallow Petrocalcic paleudolls (0.5-0.7m). The critical period is 20 d before to 30 d after anthesis. Double-headed arrows indicate yield gap due to soil.



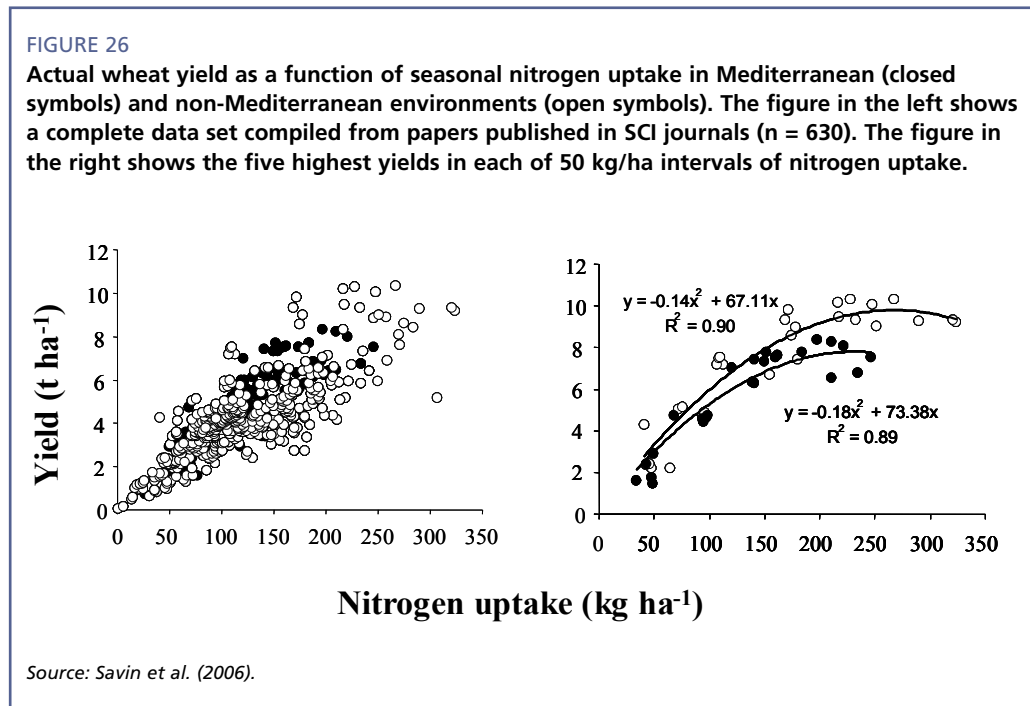
Source: Calviño *et al.* (2003).

4.2.2. Yield gaps and nitrogen uptake

Benchmarks based on capture of nitrogen are agronomically, economically and environmentally relevant in a context of increasing energy and fertiliser price and concerns with nitrogen leaching and greenhouse emissions.

Savin *et al.* (2006) used the relationship between actual wheat yield and nitrogen uptake to investigate putative differences in nitrogen use efficiency between Mediterranean and non-Mediterranean environments (Figure 26). Boundary functions revealed a lower efficiency in Mediterranean environments hypothetically associated with hotter conditions during grain filling. The curves in Figure 26 are empirical, and similar to the approach based on water use (Section 4.2.1.1 to 4.2.1.4), they account for the seasonal capture of a major crop resource. A significant part of the gap between actual and attainable yield is accounted for grain nitrogen concentration (Savin *et al.* 2006; Ciampitti & Vyn 2012), which constrains the application of this approach to benchmarking.

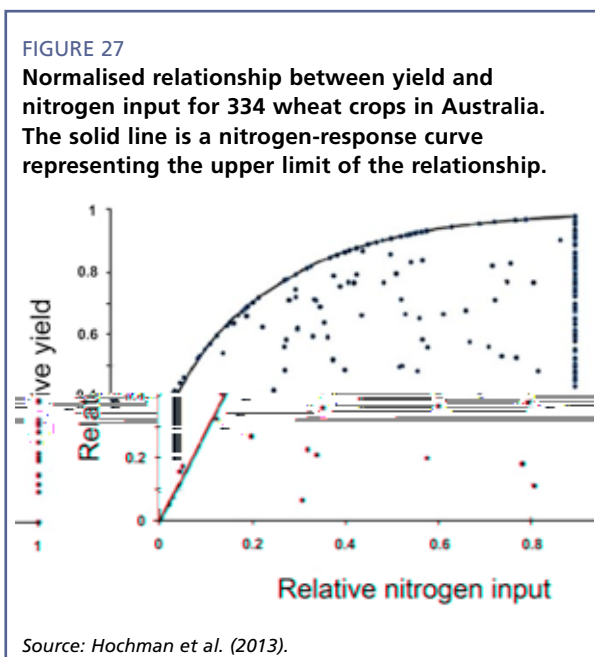
Hochman *et al.* (2013) use a nitrogen-based benchmark to estimate yield gaps in rainfed wheat crops in Australia. They compiled a data set of yield and nitrogen use, calculated as the sum of crop nitrogen uptake and nitrogen lost to the root zone, and derived a normalised boundary function based on a representative nitrogen response



curve (Figure 27). The normalisation estimates the shortfall in nitrogen input of the actual crop relative to the input required to reach yield potential. The analysis indicated 64% of crops attained actual yields that was within 80% of the expected yield as simulated using the actual input of nitrogen for each crop.

Ciampitti and Vyn (2012) fitted boundary functions to characterise the relationship between yield and nitrogen uptake of maize in a comparison of old (1940 to 1990) and new (1991 to 2011) technologies using a comprehensive, worldwide database. The boundary functions were fitted with linear + plateau models with three parameters. All three parameters differed with technology: the rate of change in yield with increasing nitrogen uptake increased from 74 kg grain per kg N with old technology to 93 kg grain per kg N with new technology, the nitrogen required to maximise

yield was reduced from 181 kg N per ha to 168 kg N per ha, and maximum yield increased 13 to 16 t ha⁻¹. These boundary functions could be used for yield gap analysis, although this was not the original aim of this study, and shifts in parameters highlight the importance of proper definitions of technological background.



4.2.3. Yield gaps and soil constraints

Casanova *et al.* (2002) measured yield gaps of irrigated rice in the Ebro Delta of Spain using a soil-focused approach. They measured yield (y) and soil texture and chemical properties (x_i) in 50 fields. A boundary line was defined for each x_i variable according to the following steps: (a) each x_i was categorised in 10 groups, (b)

frequency distributions of yield for each x_i were tested for normality, (c) for groups passing the normality test the average x_i and yield at 95% confidence are selected, and (d) a linear regression is fitted using selected x_i and yield. This approach generated boundary lines with positive slope for resource-type variables, such as cation exchange capacity, and with negative slopes for constraint-type variables such as salinity. Yield was estimated as:

$$y = \text{Min} [f(x_1), f(x_2) \dots f(x_n)]$$

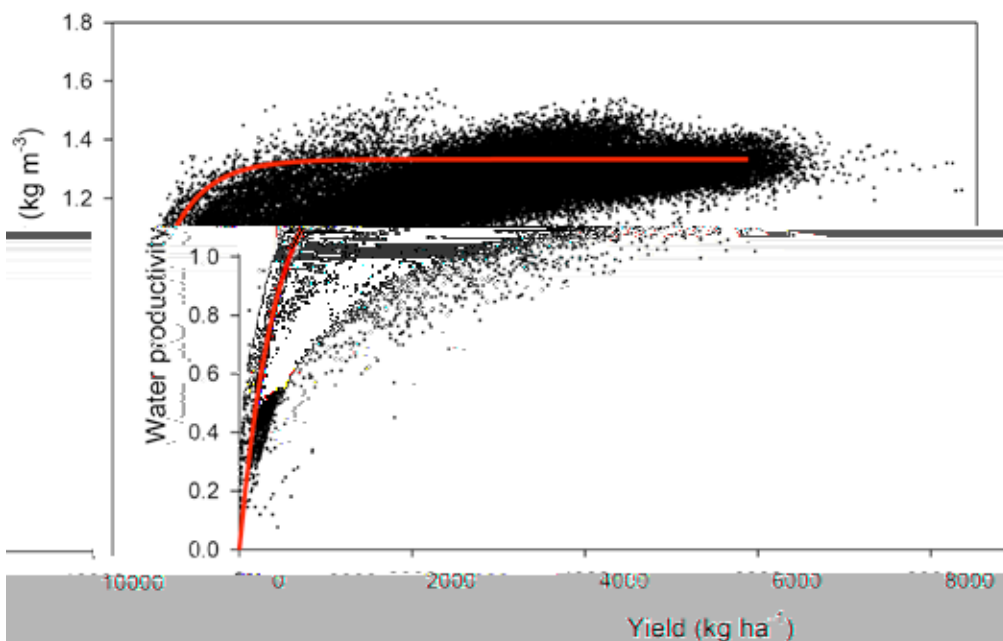
where $f(x_i)$ is the maximum yield for independent variable x_i . This approach identified three main variables, namely topsoil cation exchange capacity, soil salinity and pH which collectively accounted for a yield gap of 2.9 t ha^{-1} relative to attainable yield in the region around 11 t ha^{-1} . A residual gap of 0.8 t ha^{-1} corresponded to other, unidentified factors. A variation of this method opened up the “black box” of yield into numerical yield components (panicles per m^2 , spikelets per panicle, fraction of filled panicles and individual grain mass) and accounted for crop status variables, i.e. crop establishment, duration and nutrient status. This approach is particularly interesting for local studies of soil constraints.

4.2.4. Water productivity as a function of yield

Water productivity increases non-linearly with grain yield, as shown for example in rainfed and irrigated wheat crops in the USA (Musick *et al.* 1994). The analysis in Figure 28 for maize in Doukkala Irrigation Scheme of Morocco illustrates how boundary functions could be used to capture the upper limit of water productivity, identify underperforming fields and calculating water productivity gaps; this approach has not

FIGURE 28

Relationship between water productivity (yield per unit evapotranspiration) and yield of maize in the Doukkala Irrigation Scheme, Morocco. The red line is the boundary function fitted by calculating the 90th percentile of water productivity for yield split in 1000 kg/ha intervals. Both yield and water productivity were derived with methods combining remote sensing and modelling.



Source: Goudriaan and Bastiaanssen 2013.

been documented, but we suggest it could be useful for gap analysis where the focus is water productivity.

4.3. APPROACH 3: MODELLING

Approach 1 and 2 underestimate maximum yield where best practice is not feasible; for example, where policy or infrastructure limitations prevent the use of inputs such as fertiliser. In this section we compile a series of case studies including a comparison of yield benchmarking and gap analysis using on-farm yields (Approach 1) and modelled yield (Approach 3) with Maize in USA and Kenya, and wheat in Australia. Other case studies deal with rice in Southeast Asia, maize in Zimbabwe, quinoa in Bolivia. The use of climatic indices to estimate yield potential and FAO's Agro-Ecological Zones system are outlined.

4.3.1. Maize (USA, Kenya) and wheat (Australia)

Van Ittersum *et al.* (2013) assessed the implications of using different methods based on simulated or actual yields for yield gap assessment at a local level. The following methods were evaluated for their ability to estimate potential yield or water-limited yield for irrigated and rainfed cropping systems, respectively, and their corresponding yield gaps, across farmer's fields over relatively small geographic areas:

- site-specific simulation of potential or water-limited yield using crop growth models;
- derivation of potential or water-limited yield from upper percentiles of farmer yield distributions;
- maximum yields measured in experimental stations, growers contests, or highest-yielding farmer's fields.

Three cropping systems of varying level of intensification were considered for the analysis: rainfed maize in western Kenya, irrigated maize in Nebraska (USA), and rainfed wheat in Victoria (Australia). Year-specific 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. Detailed descriptions of cropping systems, structure and validation of crop models, and data inputs can be found in previously published studies (Grassini *et al.* 2011; Tittonell *et al.* 2006; Hochman *et al.* 2009).

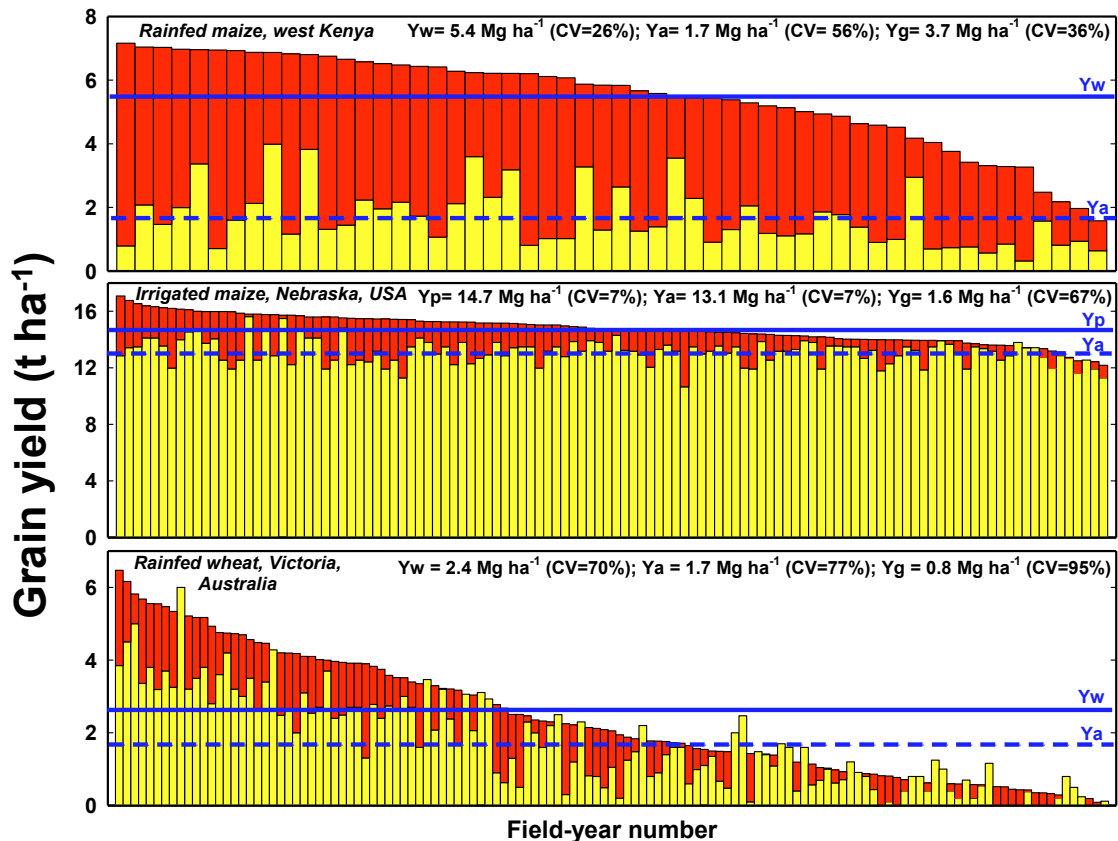
Owing to the capacity to capture major interactions among weather, soils and management, crop modelling appeared to be the most reliable way to estimate potential yield and water-limited yield for each specific crop within the defined cropping system. The attributes for a model to be useful in this type of study have been discussed in Section 3.3. Models allowed for probability distributions rather than single values of potential and water-limited yield and yield gap (Figure 29). Variability in simulated potential and water limited yield reflected not only differences in management practices among fields, but also variability in weather across years and fields. Under such conditions, farm managers face large uncertainty about yield-affecting conditions, and hence appropriate level of inputs in the season ahead (Box 2). If inputs are applied in excess of amounts needed for maximum profit in a year when potential or water limited yield is below average, closing a small yield gap will likely not meet their economic goals. On the other hand, if farmers invest too little inputs in a year with high potential or water-limited yield, the yield gap will be large and they will miss the possibility of high profit.

This was the case for rainfed maize and wheat cropping system in Kenya and Australia, although there are differences between these systems (Figure 29). While Australian farmers face greater uncertainty about water limited yield, 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. As a result, yield gaps were much smaller in rainfed wheat in Australia compared to rainfed maize in Kenya (yield gap-to-actual yield ratio of 0.4 and 2.2, respectively) (Figure 29). In the case of irrigated maize in Nebraska, access to irrigation water compensates for weather variability and associated risk, allowing growers to fine tune their management and achieve small gaps (yield gap-to-actual yield ratio of 0.1) (Figure 29).

Estimates of yield potential, water limited yield and yield gap based on maximum yields or an upper yield percentile are static or non-spatially explicit, unless they are linked with some environmental variable. A single estimate of potential or water limited yield

FIGURE 29

Simulated potential yield (Y_p) or water-limited yield (Y_w) 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 portions of the bars indicate actual farmer's yield (Y_a) and yield gap (Y_g), respectively. Horizontal lines indicate average Y_p (or Y_w) and Y_a (solid and dashed lines, respectively) for the region. Means and coefficients of variations (CV) for Y_p (or Y_w) and Y_g are shown. Fields were sorted from highest to lowest Y_p or Y_w . Note that $Y_a > Y_w$ for some site-years in Victoria which reflects incorrect specification of model inputs, actual yields, and/or inability of crop models to portray specific genotype x environment x management interactions.



Source: van Ittersum et al. (2012).

used as a reference in gap analysis does not reflect the full range of conditions within an agro-ecological zone and cropping system. The yield achieved by a contest winner or in the highest-yielding fields in any region or season was unattainable by most other farmers who did not benefit from the same climatic or soil conditions. Likewise, measured yields in experimental stations can also be biased if soil and topography (i.e. deep, fertile soils on flat land or on well terraced slopes) do not represent the surrounding production systems. Hence, maximum yields and upper yield percentiles provide an estimate of the best G x E interaction across a large population of site-years, rather than a measure of long-term average potential or water limited yield. Although all these empirical methods are convenient when data are lacking to calibrate and validate a crop model and to run it for a range of fields and years, they gave inconsistent estimates of potential and water limited yield compared to those obtained from crop simulation. In the case where actual yield was high, which indicates favourable growing conditions and little stress (i.e. irrigated maize in Nebraska), there was relatively close agreement among yield potential, water limited yield and yield gap estimates based on maximum yields or upper percentiles and estimates based on crop simulation (Table 3). In contrast, there was very poor agreement among these estimates in cases where farmers did not (or could not) use best management practices and thus achieved low yields (i.e., Kenya rainfed maize). Likewise, estimates of potential and water limited yield based on maximum yield or upper percentiles can be biased by atypical years or farms amongst the observations, but this cannot be defined without more detailed analysis using simulation models. This problem played a role in the dataset for rainfed wheat in Victoria in which the average maximum yield and the average 95 and 99 percentiles

TABLE 3

Actual average farmer yield (Y_a) and estimates of average potential yield (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 Y_a , and maximum yields. 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 (t ha ⁻¹)	Rainfed maize, western Kenya	Irrigated maize, Nebraska, USA	Rainfed wheat, Victoria, Australia
Actual yield (Y_a)	1.7	13.2	1.9
Yp or Yw based on:	Y_w	Y_p	Y_w
Simulation model	5.4	14.9	2.6
Upper percentiles Y_a:			
95 th percentile	3.6	14.4	3.5
99 th percentile	3.9	14.8	4.1
Maximum Y_a ^a	6.0	17.6	4.3
Yg based on:			
Simulation model ^b	3.7 (Yg:Y _a = 2.2)	1.6 (Yg:Y _a = 0.1)	0.8 (Yg:Y _a = 0.4)
Upper percentiles Y_a:			
95 th percentile	1.9 (Yg:Y _a = 1.1)	1.1 (Yg:Y _a = 0.1)	1.9 (Yg:Y _a = 1.0)
99 th percentile	2.2 (Yg:Y _a = 1.3)	1.6 (Yg:Y _a = 0.1)	2.2 (Yg:Y _a = 1.2)
Maximum Y_a	4.3 (Yg:Y _a = 2.5)	4.5 (Yg:Y _a = 0.3)	2.3 (Yg:Y _a = 1.2)

^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 fields (rainfed wheat in Victoria).

^b For Australia, when $Y_a > Y_w$, $Y_g = 0$ was assumed.

Source: van Ittersum *et al.* (2013).

of farmers yields across three years was well above the average simulated water-limited yield over the same period (Table 3). If the maximum yield and 95 and 99 percentiles of farmers yields had been taken from the entire population of field-years, aggregated across years, the difference between simulated Y_w and the 95 and 99 percentiles would be substantially higher as the best year would have been used as the benchmark.

4.3.2. Rice in Southeast Asia

Laborte *et al.* (2012) analysed farmers' yields and yield gaps in the wet and dry seasons in four intensively cropped rice areas in Southeast Asia: Central Luzon, Philippines; West Java, Indonesia; Suphan Buri, Thailand; and Can Tho, Vietnam. Yield gaps were estimated based on potential yield derived from the crop growth model ORYZA2000 applying crop development rates calculated from observed phenological stages, actual crop establishment methods and actual average planting dates of farmers (Bouman 2011).

Exploitable yield gaps (Section 2.2) were estimated based on economic (80% of potential yield) and best farmers' yields (upper 10 percentile in each year, season, and site). They found yield differences of 2.6–5.4 t ha⁻¹ between average and potential yields, 1.0–3.6 t ha⁻¹ between average and economic yields, and 1.1–2.3 t ha⁻¹ between average and best farmers' yields. The gap between average and best yields was higher in rice-importing countries (Indonesia and Philippines) compared with rice-exporting countries (Thailand and Vietnam).

Many yield gap studies consider a single year or period (Section 3.2.1). In addition to looking at yields and yield gaps across sites, this study evaluated yield differences across time using four decades of farm survey data (1966 to 2008) for Central Luzon, Philippines. They used quantile regression to estimate annual increments in yields that correspond to various percentage points of the distributions of farmers' yields. From 1966 to 1979, annual increases in rice yields for farmers in the upper quantiles were much higher than those in the lower quantiles as yield increased with adoption of higher-yielding modern rice varieties by some farmers. On the other hand, there was no significant change in yields for the lowest 10 percentile despite more than a decade since the introduction of modern rice varieties. Owing to the differential rate of adoption of new technology between leading and average farmers during this period, the gap between average and best yields increased with time (Figure 11). From 1982 onwards, the lower 30 percentile had slightly higher annual increments than others, as farmers with low yields started to adopt modern rice varieties. However, the mean gap between average and best yields for surveys conducted during the 2000s did not differ much from that of the 1980s.

Closing the yield gap in farmers' fields in Southeast Asia remains a challenge. Best farmers' yields were already near to, or in some cases, even higher than their estimate of economic yield. This implies that it will not be economically attractive for best-yielding farmers to further increase yields, unless there is a change in the prices of rice and/or production inputs to warrant more investment. On the other hand, the gap between average and best yields could still be reduced, especially in the rice importing countries, where the gap is larger. This study gave indications of some causal factors by comparing some characteristics of and production inputs used by average and best yielding farmers. To bridge the gap, production inputs such as fertiliser and labour should be used more efficiently and intensive knowledge delivery and programs that enhance farmers' skills as well as institutional arrangements are vital.

4.3.3. Maize in Zimbabwe

Kahinda *et al.* (2007) used a simulation model (APSIM) to investigate alternative cropping practices to close the yield gap of maize in semi-arid Zimbabwe. They estimated two extreme yields, i.e. maximum with good supply of water or nitrogen, and a rainfed control closer to standard practices with no fertiliser and no supplemental irrigation. Within the boundaries of these extreme yields, a range of feasible options were modelled, e.g. modest amounts of inorganic nitrogen or manure in combination with locally developed rain water harvesting techniques. This modelling exercise showed the synergy between water and nitrogen, which is consistent with theoretical and empirical considerations (Sadras 2005; Cossani *et al.* 2010).

4.3.4. Quinoa in Bolivia

Geerts *et al.* (2009) used the AquaCrop model to examine the potential of closing quinoa yield gaps using irrigation in the Bolivian Altiplano, where yields of rainfed crops are low and unstable. Simulated scenarios included a rainfed control, a reference strategy avoiding stomatal closure during all sensitive growth stages and allowing drought stress during the tolerant growth stages and various restrictive deficit irrigation strategies representing cases when water resources are limited. From the scenario analysis, probability curves were derived for three agro-climatic regions. The modelled yields of rainfed quinoa during dry years ranged from 1.1 t ha⁻¹ in the northern region to 0.2 t ha⁻¹ in the southern Altiplano and increased to 2.2-1.5 t ha⁻¹ with the best irrigation treatment, corresponding to yield gaps > 1 t ha⁻¹. Minimum water availability required to significant reductions in yield gaps were identified, in the order of 600-700 m³ per ha for the central and southern regions.

4.3.5. Estimating yield potential with climate indices

Previous Sections illustrated yield gap analysis based on simulation models accounting for environment, crop and management factors. Here we outline simpler methods to account for major climate drivers in the definition of yield potential (Section 2) and their application in benchmarking. Fischer (1985) defined a photothermal quotient (PTQ) relating solar radiation (Rad) and mean temperature (T) above a base temperature (T_b) during a time window comprising the most critical period for grain set:

$$PTQ = Rad / (T - T_b)$$

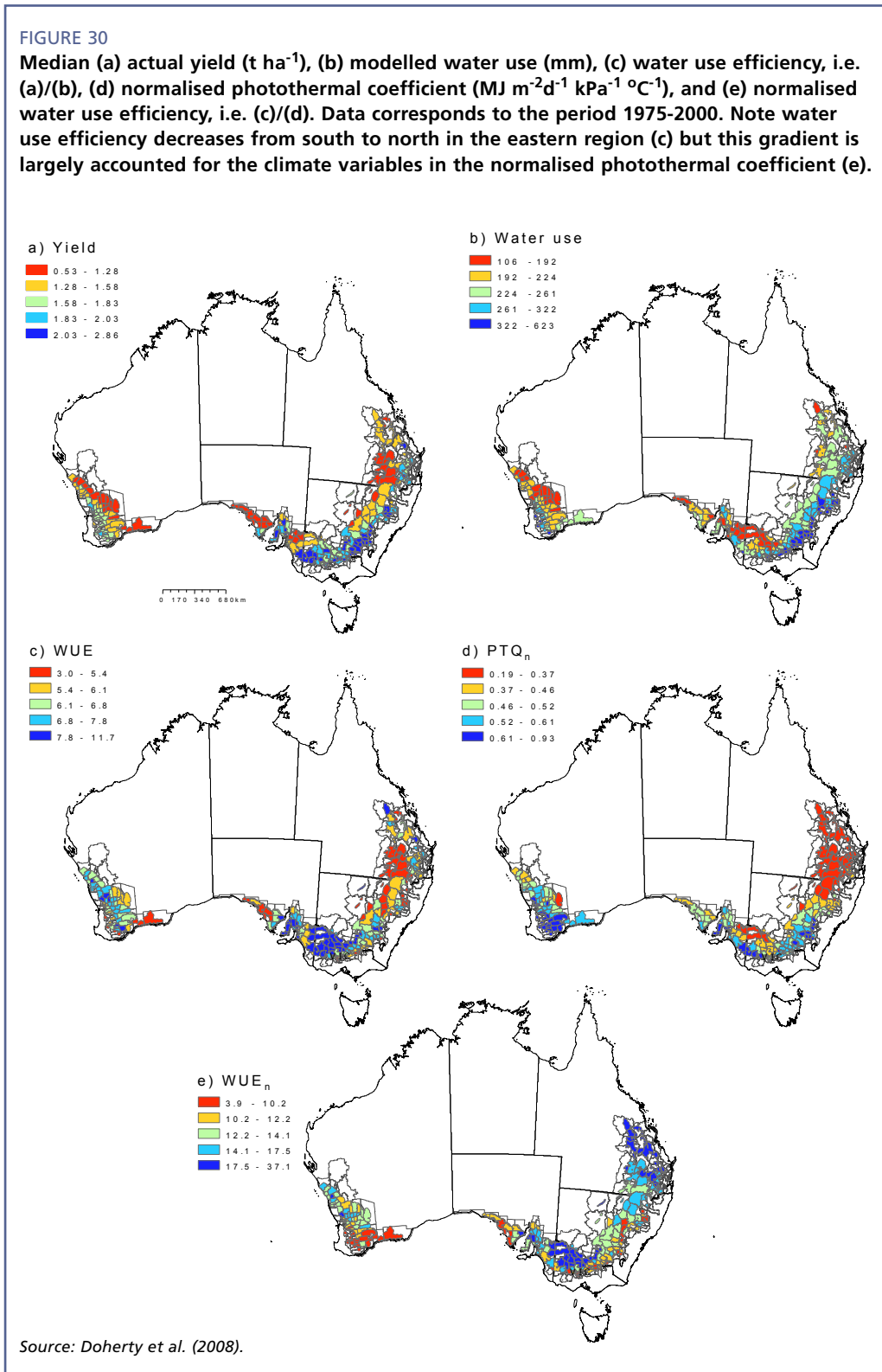
This coefficient reflects four physiological principles, namely (a) grain number is the main yield component (Sadras, 2007b), (b) grain number is proportional to total growth during a species-specific critical window around flowering (Andrade *et al.*, 2005), (c) growth rate during this critical window is proportional to photosynthesis and hence radiation, and (d) the duration of this period is inversely proportional to temperature. On these principles, Fischer's (1985) photothermal quotient and derived indices usually capture a substantial part of the variation in grain yield of diverse annual grain crops (Fischer 1985; Cantagallo *et al.* 1997). In the study of Bell and Fischer (1994) outlined in Section 3.2.2, the rate of change of wheat yield in the Yaqui Valley of Mexico calculated with the photothermal quotient was similar to the rate calculated with CERES-wheat, although estimates were offset by approx. 0.8 t. Estimates of grain number using a photothermal coefficient, and modelled (Menendez and Satorre 2007) or actual (Calviño and Sadras 2002) kernel weight were used to generate location-specific benchmarks of wheat yield in the Pampas.

Rodriguez and Sadras (2007) used a normalised photothermal coefficient (PTQ_n) accounting for the effects of photosynthetically active radiation (PAR), mean tempera-

ture (T), vapour pressure deficit (VPD) and fraction of diffuse radiation (FDR) to benchmark wheat yield in eastern Australia

$$PTQ_n = PAR * FDR / VPD * T$$

Doherty *et al.* (2008) combined actual yield, modelled seasonal evapotranspiration and the coefficient PTQ_n to produce a shire-level benchmark of attainable wheat water



productivity (Figure 30). The rationale of this approach is that the boundary water-limited yield, as determined with the French and Schultz model (Section 4.2.1.1), can be improved by accounting for physiologically relevant (a) critical period and (b) climatic drivers included in PTQn. This approach may be of interest to benchmark yield in future climates where warming and increased VPD are likely to have significant impact on water productivity (Potgieter *et al.* 2013).

4.3.6. FAO's Agro-Ecological Zones system

GAEZ refers to the Agro-Ecological Zones system, developed by FAO and IIASA (International Institute for Applied Systems Analysis). This tool enables land-use planning based on an inventory of land resources and their biophysical limitations and potential for crop production. The characterization of land resources accounts for climate, soils and landform, which are basic for the supply of water, energy, nutrients and physical support to crops. GAEZ models potential yield and downscales year 2000 statistics of main food and fiber crops to derive actual yield. The spatial resolution for yield gap analysis, derived from potential and actual yield, is 5 arc-minute. Further details can be found in: <http://www.fao.org/nr/gaez/publications/en/>

4.4. APPROACH 4: REMOTE SENSING

We emphasised the need for precision and accuracy of crop yield data for gap analysis, and highlighted some of the limitations from actual measurements, surveys, regional and national statistics and modelled yield. Indirect measurements via satellites have a potential to measure fields and regions to complement and cross check other sources of data (Box 4).

Lobell (2013) recently reviewed the application of remote sensing in yield gap analysis; thus, this Section only presents a few examples.

BOX 4

REMOTE SENSING: APPROACHES TO ESTIMATE CROP YIELD

Remote sensing is the technology of identifying, observing, and measuring an object without coming into direct contact with it. The radiometers aboard dozens of polar orbiting satellites measure the reflected, emitted and scattered radiance in small parts of the electromagnetic spectrum (visible, red-edge, near-infrared, thermal infrared, microwave, etc.). Spectral reflectance and spectral emittance measurements are combined with algorithms that convert raw data into quantitative bio-physical information at various scales, from small farm plots to large agro-holdings. The smallest scale is one pixel, and for field scale applications the pixel size often ranges from 10 m x 10 m to 30 m x 30m. The second smallest scale is a combination of a number of pixels. A group of pixels can form a soil or management unit on a farm, or can be an entire field. The frequency at which data can be measured depends on the type of satellite; combinations of different satellites are used to acquire most of these data with an interval of a few days with a resolution of 30 m x 30 m or better, provided that cloud cover is not persistent.

Approaches

Remote sensing approaches to estimate crop yield can be based on (Lobell 2013): (1) biomass production and partitioning, (2) empirical models relating spectral vegetation index and yield, and (3) integration of remotely sensed data and crop growth models.

1. Biomass production and partitioning

Biomass production can be calculated as the product between absorbed photosynthetically active radiation (APAR) and radiation use efficiency (Monteith 1977). APAR is the radiation (400 to 700 nm) absorbed by the crop and subsequently used for photosynthesis; it depends on: (i) solar radiation at the top of the atmosphere, (ii) cloud cover, (iii) atmospheric constituents that control the transmittance of radiation through the atmosphere and (iv) the size, architecture and greenness of canopies where chlorophyll captures photosynthetically active light. Cloud cover can be acquired from geostationary satellites that measure cloud brightness with small time intervals e.g. (Hammer *et al.* 2003). Remotely sensed vegetation indices e.g. (Asrar *et al.* 1992) or leaf area index (Mynemi *et al.* 2002) describe the extent of green leaves that intercept the photosynthetically active radiation. Hence, APAR can be derived totally from satellite measurements see also Baret and Guyot (1991). Various equations have been developed for the determination of radiation use efficiency, for example Field *et al.* (1995) and Hilker *et al.* (2008). As radiation use efficiency varies with crop stage, crop geometry and environmental and management factors, the assumption of a fixed efficiency could be an important source of error in estimating biomass and yield (Stockle and Kemanian 2009). The same conclusion applies to deterministic crop production simulation models and this is therefore a more general challenge in the modelling of crop yield.

Actual yield (Y_a) can be computed as a function of cumulative biomass produced during the season (ΣB), harvest index (HI) and the water content of the crop at harvest (m_{oi}):

$$Y_a = (\Sigma B \cdot HI) / (1 - m_{oi}) \quad Y_{act} = \frac{\Sigma B \cdot HI}{1 - m_{oi}}$$

Reviews on harvest index have been published by Hay (1995) and Unkovich *et al.* (2010), who emphasised the variability of this trait. Various approaches have been developed for the computation of harvest index (Sadras and Connor 1991; Ferreres and Soriano 2007; Kemanian *et al.* 2007; Raes *et al.* 2010). It is common practice to locally calibrate the harvest index and water content of the harvestable crop to ensure that fresh crop yield estimation from satellite data matches local measurements. This approach was applied by Zwart and Bastiaanssen (2007) in Mexico using harvest index values published by Lobell *et al.* (2003b). This method was followed also by van Dam and Malik (2003) in the Sirsa District of India using the official figures by the Indian Bureau of Statistics. Bastiaanssen and Ali (2003) used a similar approach which produced realistic results for wheat and sugarcane crops cultivated in the Indus Basin, Pakistan. On average, an accuracy of over 90% was achieved in the yield estimations. This can be improved further if local yield data are used in the calibration.

2. Empirical models relating spectral vegetation index and yield

Several studies used linear regression between spectral vegetation indices and crop yield. The yield data can be taken from crop cutting experiments or from secondary data sources. A single vegetation index measurement or the accumulated vegetation index for crop-specific developmental phases can be selected. The USDA method is based on the latter selection and applies essentially to cereals; it works particularly well for wheat (Hatfield 1983b). Applications in other crops include Daughtry *et al.* (1992) with maize and soybean and Steven *et al.* (1983) with sugarbeet.

3. Integration of remotely sensed data and crop growth models

Satellite measurements can be linked with crop simulation models. By comparison of model and satellite-based variables, the model updates its state conditions, remaining

more in line with the actual crop growing conditions. This complex mathematical approach is meant to estimate the production of a representative field in a given region, and is suitable for research more than to management applications. Currently, it is not feasible to apply modelling of this complexity at the scale of individual pixels. Examples of this approach can be found in Maas (1991) and Vazifedoust *et al.* (2009).

In summary, approach 1 requires standard computation procedures and is applicable across a range of physiographical conditions; assumptions on both radiation use efficiency and harvest index need local and crop specific calibration libraries that could be valid for a number of 5 to 10 years. Approach 2 generates simple solutions for particular crops provided satisfactory agreement can be found between spectral vegetation indices and crop yield, but requires repeatedly local calibrations against destructive crop yield measurements that constrain its application. Moreover, poor regression results are often found (e.g. Lyle *et al.* 2013). Approach 3 is more suitable for scientific research than applications.

4.4.1. Benchmarking crop yield and yield gaps with remote sensing

The work of Lobell and Ortiz-Monasterio (2006) and Samarasinghe (2003) are examples of the multiple and varied combinations of modelling and remote sensing that can be used in benchmarking crop yield. Lobell and Ortiz-Monasterio (2006) worked with wheat in Mexico and Samarasinghe (2003) with rice, tea, rubber and coconut in Sri Lanka. Both used a similar yield reference for gap calculations, i.e. highest yield in farmer's fields (Lobell and Ortiz-Monasterio 2006) or 95 percentile yield (Samarasinghe 2003). Lobell and Ortiz-Monasterio (2006) combined Landsat images with a temperature-based model of crop growth and Samarasinghe (2007) combined NOAA-AVHRR images with a radiation-based model of crop growth based on SEBAL ET rates and soil moisture values from Sri Lanka (Bastiaanssen and Chandrapala, 2003). Lobell and Ortiz-Monasterio (2006) further crossed-linked remote sensing data with modelled grain yield using CERES-wheat.

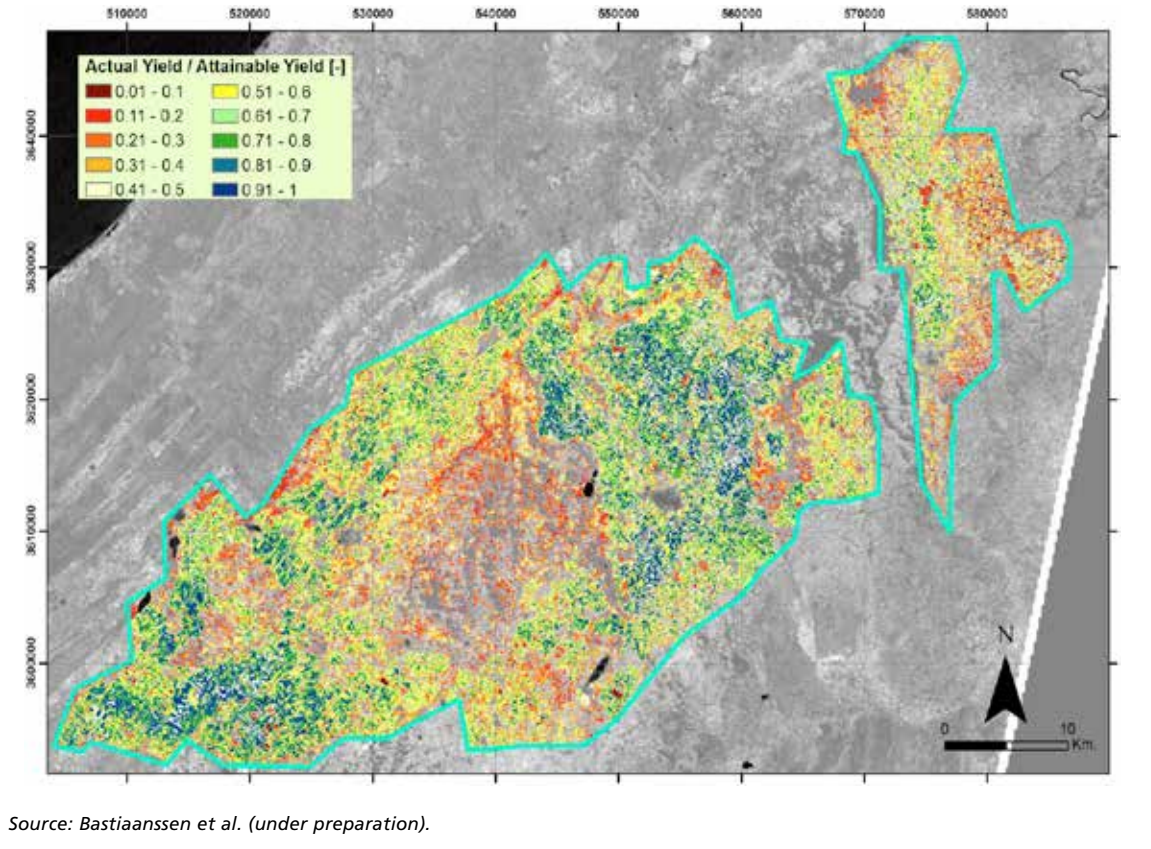
Figure 31 shows the estimated ratio between actual and attainable yield in the Doukkala irrigation scheme in Morocco, where the attainable yield is defined as the 95% percentile on the probability density function of actual crop yield. By considering this ratio in single pixels within the same agro-ecological zone, the opportunity arises to define the yield gap for all different crop types. The dominant crop types are wheat, maize, soybean and sugarbeet. The areas with a ratio lower than 0.7 are either rainfed crops, or partially irrigated crops. Indeed, the Doukkala irrigation scheme is located in the tail end of the Uom R'bia river basin system, and the scheme is in competition with water resources that are diverted to Casablanca.

4.4.2. Benchmarking water productivity with remote sensing

Remote sensing has also been used to estimate evapotranspiration with a number of methods at different scales in space and time (Hatfield 1983a; Borchardt and Trauth 2012; Jian *et al.* 2012; Ma *et al.* 2012; Poblete-Echeverria and Ortega-Farias 2012; Yang *et al.* 2012b; Yang *et al.* 2012a); details of these methods are beyond the scope of this publication. Combined with estimates of yield based on remote sensing (Box 4), these estimates of evapotranspiration allow for calculation of water productivity that is fully derived from remote sensing.

FIGURE 31

31. Spatial distribution of the ratio between actual and attainable crop yield in the irrigation scheme Doukkala in Morocco. The attainable yield is estimated as the 98% percentile of the crop yield for various crop types grown in the region.



Methods have also been developed that directly estimate water productivity without individual solutions to crop yield and evapotranspiration. Zwart *et al.* (2010) for example, reduced the inputs of the equation of water productivity to four spatial variables derived from routine satellite measurements: broadband surface albedo, normalised difference vegetation index (NDVI), extraterrestrial radiation and air temperature. The model of Zwart *et al.* (2010) was used to map wheat water productivity on a global scale. Their study was followed up by Bastiaanssen *et al.* (2010) for wheat, rice and maize at global scale level and publications are under preparation.

Gonzalez-Dugo and Mateos (2008) benchmarked water productivity of irrigated cotton and sugarbeet in an irrigation scheme comprising 15,000 ha in southern Spain. They used published boundary functions, i.e. yield vs evapotranspiration, for each crop and actual yield from local growers (Approach 2). To relate actual yield and actual evapotranspiration, reference evapotranspiration was multiplied by robust crop coefficients derived from multispectral vegetation indices, derived in turn from ground- or satellite-based radiometric measurements.

5. Conclusions and recommendations

The spatial scale selected for benchmarking should depend on the nature of the problem. For the improvement of yield at the farm scale, for example, benchmarking at the field level is required. Parallel to the spatial scale, the time scale needs consideration. If the aim is to benchmark crops under current technology, the time scale needs to be long enough to capture as much variation in seasonal conditions as possible, and short enough to meet the assumption of constant technology. A dynamic perspective allows for benchmarking that captures time trends associated with technological progress, rates of adoption and environmental change. Both static and dynamic approaches to benchmarking yield of rainfed crops need to capture the large seasonal and intra-seasonal variation of rainfall in dry environments. The diversity of benchmarking methods outlined in this publication reflects the diversity of spatial and temporal scales, the questions asked, and the resources available to answer them. We grouped methods in four broad approaches. These approaches are not rigid, and combinations of methods are common.

Approach 1 compares actual yield with the best yield achieved in comparable environmental conditions, e.g. between neighbours with similar topography and soils (Section 4.1). Comparisons of this type are spatially constrained by definition, and are an approximation to the gap between actual and attainable yield. With minimum input and greatest simplicity, this allows for limited but useful benchmarks; yield gaps can be primarily attributed to differences in management. This approach can be biased, however, where best management practices are not feasible as illustrated for maize in Kenya; modelled yields provide more relevant benchmarks in these cases (Section 4.1.3). On the other hand, current models are unsuitable to answer some questions of local relevance. For example, generic crop models are unable to capture the biophysical interactions between green manure and chemically and physically contrasting soils; the question of maize yield gaps and risks associated with these drivers in sub-Saharan Africa is thus answered with a combination of actual yield data and various models (Section 4.1.2).

Approach 2 is a variation of approach 1, i.e. it is based on comparisons of actual yield, but instead of a single yield benchmark, attainable yield is expressed as a function of one or few environmental drivers such as actual evapotranspiration. In common with Approach 1, these methods do not necessarily capture best management practices. The French and Schultz model is the archetype in this approach, and other variants include nitrogen uptake or soil properties instead of water. A boundary model fitted to the data provides a scaled benchmark, thus partially accounting for seasonal conditions. Parameters for boundary functions can be estimated with quantile regression, which requires some arbitrary assumption on the fraction of data to be used. Inclusion of remote sensing-based populations of crop yields is the way forward. A combination of empirical curve fitting and physiologically informed parameterisation has also been used. We recommend (i) using the method of Milne *et al.* as a statistically robust, objective approach to derive boundary functions (Box 3) and (ii) checking the shape and parameters of boundary functions for physiological and agronomic meaning. Where statistical and biophysical criteria conflict, we are inclined to favour biophysical criteria.

Approach 3 is based on modelling which may range from simple climatic indices such as Fischer's photothermal coefficient to intermediate models such as AquaCrop and the more complex CERES-type models. More complex models are valuable agronomically because they capture some genetic features of the specific cultivar, and the critical interaction between water and nitrogen. "Best practice" to model yield in gap analysis has been outlined (Section 3.3). Importantly, models to estimate potential yield require parameters that capture the physiology of unstressed crops. Particular attention needs to be paid to weather data used in modelling yield because significant bias can accrue from inappropriate data sources; this is illustrated for gridded global weather databases in Section 3.3.2. Studies that have used gridded weather databases to simulate potential and water-limited yields for a grid are rarely validated against simulated yields based on actual weather station data from locations within the same grid. This should be standard practice, particularly where global scale yield gaps are used for policy decisions or investment in R&D. Alternatively, point-based simulations of potential and water-limited yields, complemented with an appropriate up-scaling method, may be more appropriate for large scale yield gap analysis.

Approach 4 benchmarking involves a range of approaches combining remote sensing, actual data, and models of varying complexity (Section 4.4). These models can be applied to any pixel of 10 m x 10m or 30m x 30 m or assimilate basic remote sensing vegetation data into complex mechanistic crop growth simulation models. This approach is important for benchmarking at and above the regional scale. Remote sensing applied to yield gap analysis has improved over the last years, but significant constraints remain unsolved including the radiation use efficiency and harvest index, which require a local calibration. The vantage point of remote sensing is the production of actual yield data that facilitates the identification of local yield gaps.

Irrespective of the approach used to estimate yield and calculating yield gaps, a critical assessment of data reliability (yield, weather, agronomy) and sound understanding of the actual biophysical and agronomic background of the targeted system are essential to reduce the likelihood of misinterpretation of data. Variation of yield within fields remains a challenge for yield gap analysis.

Glossary

Precision: the extent to which a measurement procedure gives the same results each time it is repeated under identical conditions.

Accuracy: the closeness of a measurement to the true value.

Boundary function: upper and/or lower limit to the value of the response variable at any given value of the independent variable imposed by some biological mechanism so that values larger/smaller than the upper/lower boundary, respectively, are not possible (ignoring measurement error). Boundary functions are also called “envelope” functions.

Benchmark: a point of reference that serves as a basis for evaluation or comparison.

Decile: one of nine actual or notional values of a variable dividing its distribution into ten groups with equal frequencies. For example, the 9th decile is the value below which 90% of the population lie.

Percentile: one of 99 actual or notional values of a variable dividing its distribution into 100 groups with equal frequencies. For example, the 90th percentile is the value below which 90% of the population lie.

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Yield gap analysis of field crops

Methods and case studies

To feed a world population that will exceed 9 billion by 2050 requires an estimated 60% increase over current primary agricultural productivity. Closing the common and often large gap between actual and attainable crop yield is critical to achieve this goal.

To close yield gaps in both small and large scale cropping systems worldwide we need (1) definitions and techniques to measure and model yield at different levels (actual, attainable, potential) and different scales in space (field, farm, region, global) and time (short and long term); (2) identification of the causes of gaps between yield levels; (3) management options to reduce the gaps where feasible and (4) policies to favour adoption of sustainable gap-closing solutions.

The aim of this publication is to critically review the methods for yield gap analysis, hence addressing primarily the first of these four requirements, reporting a wide-ranging and well-referenced analysis of literature on current methods to assess productivity of crops and cropping systems.

This work builds on the activities of FAO and the Dougherty Water for Food Institute (DWFI) to develop tools and knowledge delivery systems to inform and guide policymakers in managing water and agriculture. Two major initiatives are at the foundation of this publication: the Global Yield Gap Atlas (led by DWFI) and the Regional Initiative on Water Scarcity for Near East and North Africa (led by FAO).

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