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From field to atlas: Upscaling of location-specific yield gap estimates

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ABSTRACT

Accurate estimation of yield gaps is only possible for locations where high quality local data are available, which are, however, lacking in many regions of the world. The challenge is how yield gap estimates based on location-specific input data can be used to obtain yield gap estimates for larger spatial areas. Hence, insight about the minimum number of locations required to achieve robust estimates of yield gaps at larger spatial scales is essential because data collection at a large number of locations is expensive and time consuming. In this paper we describe an approach that consists of a climate zonation scheme supplemented by agronomical and locally relevant weather, soil and cropping system data. Two elements of this methodology are evaluated here: the effects on simulated national crop yield potentials attributable to missing and/or poor quality data and the error that might be introduced in scaled up yield gap estimates due to the selected climate zonation scheme. Variation in simulated yield potentials among weather stations located within the same climate zone, represented by the coefficient of variation, served as a measure of the performance of the climate zonation scheme for upscaling of yield potentials.

We found that our approach was most appropriate for countries with homogeneous topography and large climate zones, and that local up-to-date knowledge of crop area distribution is required for selecting relevant locations for data collection. Estimated national water-limited yield potentials were found to be robust if data could be collected that are representative for approximately 50% of the national harvested area of a crop. In a sensitivity analysis for rainfed maize in four countries, assuming only 25% coverage of the national harvested crop area (to represent countries with poor data availability), national water-limited yield potentials were found to be over- or underestimated by 3 to 27% compared to estimates with the recommended crop area coverage of ≥50%. It was shown that the variation of simulated yield potentials within the same climate zone is small. Water-limited potentials in semi-arid areas are an exception, because the climate zones in these semi-arid areas represent aridity limits of crop production for the studied crops. We conclude that the developed approach is robust for scaling up yield gap estimates from field, i.e. weather station data supplemented by local soil and cropping system data, to regional and national levels. Possible errors occur in semi-arid areas with large variability in rainfall and in countries with more heterogeneous topography and climatic conditions in which data availability hindered full application of the approach.

1. Introduction

A major route to meet the estimated increase in future food demand of 60% by the year 2050 (Alexandratos and Bruinsma, 2012) is to derive more agricultural production from existing agricultural land. This can be accomplished by reducing the gaps between farmers' actual crop yields and yields that are possible if optimum management is adopted, the so-called 'yield gap' (Y_g, Van Ittersum

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et al., 2013). For irrigated systems, the theoretically possible yield (yield potential, Y_p) is defined as the yield of an adapted crop cultivar when grown without water and nutrient limitations and biotic stress effectively controlled, i.e. yield is determined by prevailing radiation, temperature and atmospheric [CO_2], and cultivar characteristics (Evans, 1993). For rainfed, or partially irrigated systems, Y_g is estimated based on water-limited yield potential (Y_w). Y_w is defined similarly as Y_p, but yields can be limited by water supply and distribution during the crop growth period, as well as field and soil properties that determine plant-available soil water availability. The greatest opportunities for production increases can be found in areas where average farmers' actual crop yields are less than 70% of their (water-limited) yield potential, as average national yield begin to plateau when they reach 75–85% of their yield potential due to socio-economic constraints (Cassman, 1999).

Several methodologies have been proposed and applied to estimate Y_p and Y_w and subsequently Y_g. Van Ittersum et al. (2013) compared several methodologies and concluded that the application of crop growth models allows for the most robust estimation of Y_p and Y_w. The advantage of crop models is that, if calibrated and validated adequately, they are able to reproduce genotype × environment × management (G × E × M) interactions, and, therefore, capture spatial and temporal variations in Y_p and Y_w, while other methodologies fail to do so.

In addition to adequate model calibration and validation, Grassini et al. (2015) highlight that the quality of Y_g analyses is influenced strongly by the quality of the model input data, including weather, soil, and crop management, as well as estimates of actual yield.

To increase global food production one important task is to identify regions where large increases in food production are still feasible. This can be achieved with help of accurate, quantitative and spatially explicit estimates of Y_g, thus considering the spatial variation in environmental conditions and the farming systems context in which crops are produced. Robust and spatially explicit Y_p and Y_w estimates can then be used as input to economic models to assess food security at different spatial scales, and for optimizing land use or to effectively prioritize research and policy interventions in order to close Y_g (Van Ittersum et al., 2013). Depending on the planned interventions or the economic model employed, Y_g analyses need to be carried out at spatial scales ranging from field, to sub-national, and national spatial scales. Y_g assessments for specific farmer's fields can help, for example, to plan site-specific management interventions, while quantitative information on Y_g at sub-national and national levels can support development of region- and national policies, interventions and evaluation of scenarios for optimizing food security and conservation of natural resources.

Several global data sets exist with weather (e.g. CRU (Mitchell and Jones, 2005)), soil (e.g. ISRIC-WISE (Batjes, 2012)), and crop management data (e.g. MIRCA2000 (Portmann et al., 2010)). These datasets cover the entire terrestrial surface using a defined gridded structure with a certain spatial resolution, assuming homogeneous conditions within each gridcell. To cover areas suitable for crop cultivation, data manipulation of some kind is required, e.g. kriging, because data do not exist or are not publicly available at all locations. Thus, global gridded weather datasets are typically based on data from weather stations, interpolated to locations without measurements, also in regions with low station density (see e.g. Hijmans et al., 2005). These global databases have been utilized to estimate Y_p and Y_w for the entire terrestrial land area (e.g. Rosenzweig et al., 2014). Other studies indicate, however, that the use of interpolated or modelled weather data can lead to considerable errors in crop model outcomes, due to the nonlinear equations used in crop growth models that represent important processes for crop growth and yield formation (Baron et al., 2005; Van Bussel et al., 2011; Van Wart et al., 2013a; Challinor et al., 2015). In addition, datasets describing global cropping patterns at a coarse scale (e.g. Portmann et al., 2010) do not capture the large complexity and spatial variability of observed cropping patterns. Thus, although these global studies may give valuable insight about spatial trends of estimated Y_p and Y_w and resulting Y_g across the globe, results for specific locations obtained from these global analyses are prone to large errors (Van Ittersum et al., 2013). Given this situation, achieving more accurate estimates of Y_p and Y_w at specific locations requires location-specific data with agronomic relevance to the production environment at that location (e.g. weather station data supplemented with soil and actual farm management data around this weather station). This approach can be defined as a "bottom-up approach" in which estimates at larger scale emerge from upscaling results at the smaller scale (adapted from Van Delden et al., 2011). The challenge when using a bottom-up approach is how Y_g estimates based on location-specific input data can be used to obtain Y_g estimates for larger spatial areas. Hence, insight about the minimum number of locations required to achieve robust estimates of Y_g at larger spatial scales is essential because data collection at a large number of locations is expensive and time consuming due to logistical, financial and/or technical constraints.

The first aim of this paper is therefore to present a protocol for scaling up location-specific yield potential estimates. This protocol forms the basis for upscaling in the Global Yield Gap Atlas (www.yieldgap.org), a project in which Y_g are estimated for major cereal crops and associated cropping systems in the world with local-to-global precision and relevance. The protocol includes a description of how to select representative locations for Y_g estimates and a description of the spatial framework utilized for scaling up location-specific Y_g estimates to larger spatial scales. The second aim of this paper is to assess the performance of this protocol in two ways: (1) how well the protocol performs in countries with different topography (Burkina Faso (homogeneous flat) and Ethiopia (heterogeneous topography)) in terms of required spatial coverage, and spatial coverage achieved for eight other African countries using the protocol, and, (2) the impact on simulated national water-limited yield potentials due to missing and/or poor quality data, as well as the error that might be introduced in scaled-up yield potential estimates due to the selected climate zonation scheme used for upscaling (see Van Wart et al., 2013c). Issues related to data requirements and adequate data sources for location-specific Y_g estimates are discussed in a companion paper (Grassini et al., 2015).

2. The Global Yield Gap Atlas protocol for upscaling

To use location-specific Y_p and Y_w as a basis for Y_p and Y_w estimations at larger spatial scales, it is essential to increase the extent of these location-specific Y_p and Y_w estimates. Extent is defined in this context as the area for which the Y_p and Y_w simulations were carried out (Bierkens and Finke, 2000). In the Global Yield Gap Atlas increasing the extent has been done with help of linear aggregation, i.e. calculating the weighted arithmetic mean of all location-specific simulations that fall within a certain area (Heuvelink and Pebesma, 1999). The efficiency of this aggregation can be improved by stratifying the area of interest (Brus, 1994).

Location-specific data required for crop models to simulate Y_p and Y_w are only available for a limited number of locations (Ramirez-Villegas and Challinor, 2012). In the present study it is therefore described how to optimize selection of locations for Y_g analyses following the underpinning principle that a reasonable number of locations should be selected that best represent how a given crop is produced in terms of production area with similar weather, soils, and cropping system. Next, the spatial framework for aggregation is described. It is used to define the spatial boundaries for robust aggregation of location-specific Y_g estimates, making use of a climate zonation scheme supplemented by guidelines for selecting the location of data collection (see Fig. 1 for a schematic overview). A similar approach has previously also been applied by, among others, Wolf and Van Diepen (1995) and Wang et al. (2009) to assess climate change impacts on maize yields in Europe and farming systems performance at catchment and regional scales, respectively.

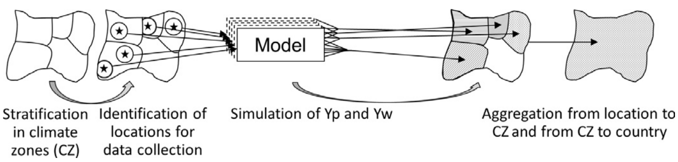

Fig. 1. Schematic overview of the Global Yield Gap Atlas upscaling protocol (after Ewert et al., 2011).

2.1. Site selection

Robust Y_g analyses should account for variations in weather conditions across years. This can only be achieved if high quality location-specific weather data for at least 10, but preferable at least 15 years are available (Van Wart et al., 2013b; Grassini et al., 2015). Consequently, our site selection was guided by the location of existing weather stations, to make full use of available weather data, especially in Sub-Saharan Africa where weather stations providing data with sufficient quality and quantity are scarce (Ramirez-Villegas and Challinor, 2012; Thornton et al., 2014).

Weather stations with sufficient data quality and quantity, mainly operated by national meteorological services, were selected by using the geospatial distributions of harvested areas of the crops of interest, which were derived from the global spatial production allocation model (SPAM2000; You et al., 2006, 2009). SPAM2000 provides gridded data (5 arcmin resolution, approximately 10×10 km at the equator) on annual harvested area averaged for years around 2000 for 20 major staple crops, for rainfed and irrigated water regimes. For each grid, we calculated the harvested area of rainfed crops as the sum of the harvested area reported for three input systems, i.e. subsistence, low, and high, while the harvested area of irrigated crops was taken directly as given in the SPAM2000 database. SPAM2000 was selected because it applies a consistent methodology using available data on harvested crop area from different sources (e.g. FAOSTAT, 2014 and national statistics) to derive global spatially disaggregated harvested area maps. In the Global Yield Gap Atlas for specific cases where area for a specific crop has expanded substantially or moved into new areas since year 2000 and reliable sub-national statistics on crop harvested area were available, SPAM2000 data was replaced by these data (e.g. sugarcane in Brazil and soybean in Argentina).

A recent study in countries with relatively uniform topography indicated that 40–50% of the national harvested crop area should be covered to achieve a robust estimate of Y_p and Y_w at the national level (Van Wart et al., 2013b). To comply with this finding and the principle of using representative locations for most dominant weather–soil-cropping systems, the following steps were carried out for each country-crop combination:

(1) Circular buffer zones with a 100 km radius were drawn around each identified weather station and clipped by country and climate zone border (see Section 2.2 for more details about the climate zonation).
(2) The SPAM2000 crop-specific harvested area, for a given water regime, was summed for each climate and buffer zone.

(a) Per country climate zones were identified which contain >5% of the total national harvested crop area of the specific crop–water regime, further referred to as designated climate zones (DCZs).
(b) We identified all weather stations located within the DCZs that contain >1% of national harvested area for the crop in question within their buffer zone and checked their data quality (see Grassini et al., 2015 for more information about this quality check).
(c) Next an iterative process was carried out of:
  (i) ranking selected weather stations, according to their clipped harvested crop area within their buffer zones;
  (ii) selecting the weather station with greatest harvested area; selected weather stations are further referred to as reference weather station (RWS);
  (iii) removing weather stations that are located within the same DCZ and closer than 180 km to the selected RWS, to avoid double counting of crop area, and re-ranking the remaining weather stations; and
  (iv) repeating i–iii above until total harvested area in buffer zones of selected RWS reached 50% of the national harvested area for the targeted crop-water regime.
(d) If, after achieving 50% coverage, there was a DCZ that did not contain a selected RWS, the highest ranked weather station within that DCZ was selected (again, having >1% of national harvested area to qualify).
(e) If, after selecting among weather stations within DCZs, there was still less than 50% coverage, we selected among weather stations located in other climate zones with <5% of national crop area (again, having >1% of national harvested area to qualify).
(f) If, after step 2e, there was still less than 50% coverage of the crop-water regime, locations for so-called hypothetical weather stations (also further referred to as RWS, and with circular buffer zones with a 100 km radius) were determined in DCZs. Their location was determined with help of the Focal Statistics toolbox of the ESRI ArcMAP software, by selecting locations in DCZs with the largest cropping area density within their 100 km around the location (excluding locations situated closer than 180 km to a RWS). To derive weather data for hypothetical RWS, accompanying gridcells were selected from the gridded TRMM dataset (Simpson et al., 1996; http://trmm.gsfc.nasa.gov/) and gridded NASA POWER database (Stackhouse, 2014; http://power.larc.nasa.gov/).

2.2. Climate zonation scheme used for upscaling

Consistent with the weather station locations guiding site selection within a country, a climate zonation scheme was used as the basis for upscaling from the RWS buffer zone to larger spatial scales. Location-specific Y_p and Y_w estimates for the buffer zones were scaled up to climate zones and subsequently to the national level (Fig. 1).

The utilized climate zonation scheme (Global Yield Gap Atlas Extrapolation Domain (GYGA-ED, Fig. 2 shows the zones for Sub-Saharan Africa)) was selected based on a recent study in which six agro-climatic and agro-ecological zonation schemes were compared for their homogeneity of climatic variables within delineated climate zones (Van Wart et al., 2013c). In addition, the number of zones required to cover a large proportion (80%) of the crop-specific global harvested area of major food crops was considered. After evaluation of these two criteria it was concluded that the GYGA-ED approach was most suited for scaling up location-specific Y_p and Y_w estimates (Van Wart et al., 2013c).

The GYGA-ED climate zonation is based on a matrix of three climatic variables relevant for crop production: (i) growing degree days (base temperature of 0 °C, divided into 10 classes), (ii) aridity index (ratio of mean annual precipitation to annual potential

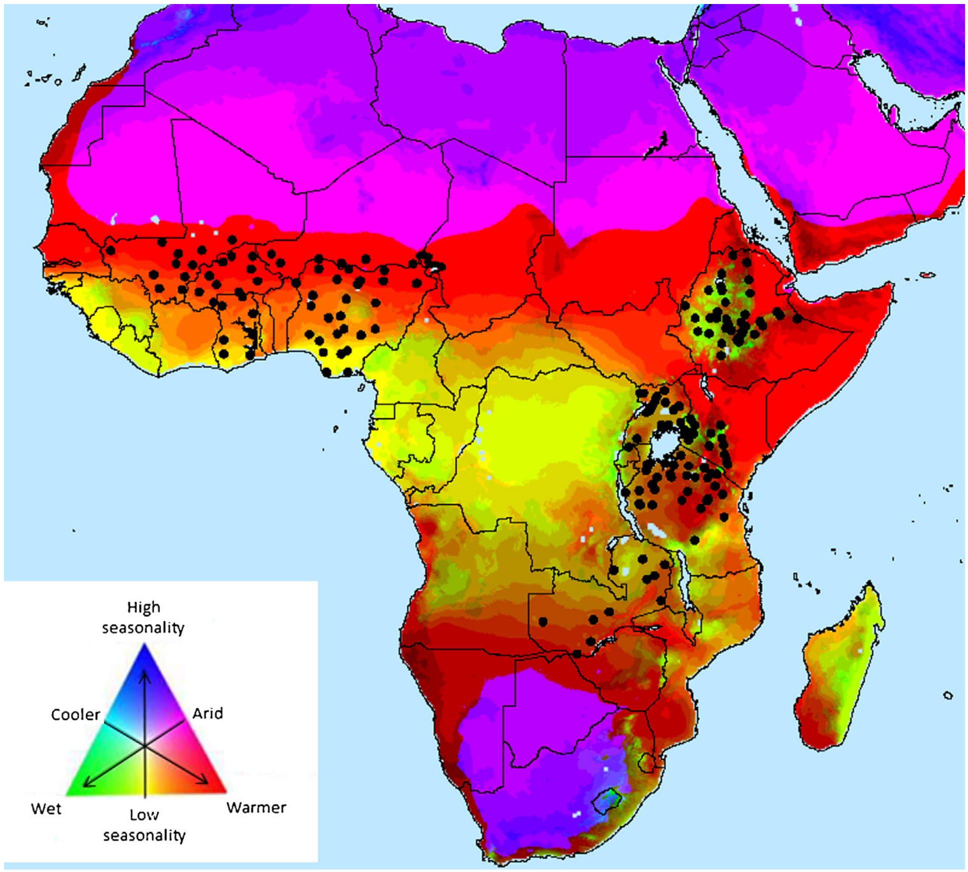

Fig. 2. The Global Yield Gap Atlas climate zonation scheme for Sub-Saharan Africa, black dots indicate locations of RWSs used for Y_g assessments in ten countries.

evapotranspiration, divided into 10 classes) and (iii) temperature seasonality (standard deviation of monthly average temperatures, divided into 3 classes). Only land on which at least one of the 10 major food crops is grown (the sum of the major food crops >0.5% of the gridcell area) was considered for the classification of the three variables (using the SPAM2000 database; You et al., 2006, 2009). In 265 of the 300 possible climate zones major foods are grown (see for more details Van Wart et al., 2013c).

2.3. Additional data collection within buffer zones

Within the circular buffer zones with a 100 km radius around the RWSs the most prominent soil type × cropping system combinations for the different water regimes (rainfed and/or irrigated) were collected. Focussing on the buffer zones gave the opportunity to simulate existing soil type × cropping system combinations, this facilitated evaluation of the simulations.

Per buffer zone, the three prevalent soil types were selected. In countries where there is availability of high-quality soil maps with functional soil properties (e.g. Argentina) these were used. If no high-quality soil maps with functional soil properties were available the global soil database ISRIC-WISE was utilized (Batjes, 2012). From the ISRIC-WISE soil database the three main map units (each comprising up to eight soil units) were selected. Selection was based on the coverage of harvested crop-specific area by a given soil map unit within the RWS buffer zone. Soil units from the selected map units were selected until achieving 50% area coverage for each selected map unit, after discarding those soils that are likely not suitable for long-term annual crop production or that account for a very small fraction of the crop harvested area (see Grassini et al., 2015, for the definition of non-suitable soil types). Information about the most commonly used cultivars (in terms of length of growing season in days) and their sowing dates for the crop in question were obtained from local agronomic experts (see Grassini et al., 2015, for more detail). Together with the weather data, this information was used to estimate location-specific Y_p and/or Y_w by simulation.

2.4. From weather station to climate zone to country

Four aggregation steps were required to derive long-term Y_p and Y_w at RWS level: by soil type (only for Y_w), by crop intensity (e.g. how often a crop is grown on a certain field during the same year), by cropping system (i.e. when cultivars with different maturity were simulated for the same RWS, e.g. early and late maturity sorghum), and by year.

To obtain the yield per crop cycle, the weighted average of the individual simulations per soil type i ($Y_{w\ \text{simulation}_i}$ was calculated as follows:

$$Y_{w\ \text{crop cycle}} = \frac{\sum_{i=1}^{n} Y_{w\ \text{simulation}_i} \times \text{Soil}_{\text{weight}_i}}{\sum_{i=1}^{n} \text{Soil}_{\text{weight}_i}} \quad (1)$$

where n is the number of soil types and $\text{Soil}_{\text{weight}_i}$ is the harvested area of soil type i.

To obtain the yield per cropping system, the average of the individual crop cycles was calculated, all cycles have the same weight, because we assume that within a cropping system all cropland has the same cropping intensity (single, double or triple cropping):

$$Y_{w\ \text{cropping system}} = \frac{\sum_{i=1}^{z} Y_{w\ \text{crop cycle}_i}}{z} \quad (2)$$

where z is the number of crop cycles, e.g. two in the case of maize-maize.

To derive the yield per year, the weighted average of all individual cropping systems was calculated, the weight of the systems was defined with help of the harvested area per system as reported by local agronomists:

$$Y_{w\ \text{year}} = \frac{\sum_{i=1}^{k} Y_{w\ \text{cropping system}_i} \times \text{Area}_{\text{cropping system}_i}}{\sum_{i=1}^{k} \text{Area}_{\text{cropping system}_i}} \quad (3)$$

where k is the number of cropping systems, e.g. two in the case of the use of early and late maturity maize within the same RWS buffer zone.

To get the yield per station, the average of all years was calculated:

$$Y_{w\ \text{station}} = \frac{\sum_{i=1}^{p} Y_{w\ \text{year}_i}}{p} \quad (4)$$

where p is the number of years (at least 10 years, see Grassini et al., 2015).

One additional aggregation step was required to derive long-term Y_p, Y_w, and Y_a at climate zone level:

$$Y_{w\ \text{climate zone}} = \frac{\sum_{i=1}^{q} Y_{w\ \text{station}_i} \times \text{Area}_{\text{RWS buffer zone}_i}}{\sum_{i=1}^{q} \text{Area}_{\text{RWS buffer zone}_i}} \quad (5)$$

where q is the number of RWSs within the climate zone and $\text{Area}_{\text{RWS buffer zone}_i}$ is the harvested area in buffer zone i.

A final aggregation step was required to derive long-term Y_p, Y_w, and Y_a at country level:

$$Y_{w\ \text{country}} = \frac{\sum_{i=1}^{s} Y_{w\ \text{climate zone}_i} \times \text{Area}_{\text{climate zone}_i}}{\sum_{i=1}^{s} \text{Area}_{\text{climate zone}_i}} \quad (6)$$

where s is the number of climate zones within the country and $\text{Area}_{\text{climate zone}_i}$ is the harvested area per climate zone i.

3. Methods to assess the upscaling protocol

Performance of the protocol was assessed by: (1) evaluating the influence of the spatial coverage of harvested area by RWS buffer zones on national Y_w, and (2) assessing the selected climate zonation scheme to upscale Y_w and Y_p estimates at RWS scale to larger spatial scales.

3.1. Application and spatial coverage

The first phase of the Global Yield Gap Atlas project focussed on ten countries in Sub-Saharan Africa: Mali, Burkina Faso, Ghana, Niger, Nigeria, Ethiopia, Kenya, Tanzania, Uganda, and Zambia. Only cereal crops (maize, sorghum, millet, rice, wheat) with a total national harvested area of >100,000 ha (area threshold applied separately to rainfed and irrigated production) were evaluated. Maize was simulated with the crop growth model Hybrid-Maize (Yang et al., 2006), sorghum, millet, and wheat with WOFOST version 7.1.3 (release March 2011) (Wolf et al., 2011; Supit et al., 2012), and rice with ORYZA2000 (Bouman et al., 2001; Van Oort et al., 2014, 2015).

To test how well the protocol could be applied in these ten countries, it was evaluated to what extent we could comply with the protocol. This assessment was performed for rainfed sorghum in two countries with contrasting topography and climate zone size: Burkina Faso (homogeneous flat and large climate zones) and Ethiopia (heterogeneous topography and small climate zones), for Y_w. In addition, the uncertainty in the estimated Y_w at national level for rainfed maize in four contrasting countries (Burkina Faso, Ghana, Uganda, and Kenya) due to harvested area coverage was evaluated. We focused on Y_w because we expected the Y_w at national level to be more sensitive to the harvested area covered than the national Y_p. First, the area-weighted Y_w at the national scale was calculated by incrementally adding all estimated Y_w's per RWS, which were sorted based on the harvested area within their buffer zone, from large to small. Second, to test the effect on the national Y_w estimate of a smaller harvested area covered by the RWS buffer zones, a random selection from all estimated Y_w's at RWS level was carried out, till at least 25% coverage of the national harvested area was reached by the RWS buffer zones, i.e. half of the required coverage. From these randomly selected Y_w's the national Y_w was calculated. This selection process was carried out 10 times. The difference between the highest and lowest of these 10 national Y_w's was calculated, as an indication of the robustness of the Y_w at national level with a smaller coverage.

3.2. Assessment of the climate zonation scheme

The described protocol is based on the assumption that for the purpose of crop growth modelling weather data from RWSs are representative for the climate zone in which they are located. To test this assumption, we selected climate zones in the U.S., Germany, and Western Africa that have, at least, three RWSs located within their borders. For the evaluation of the climate zonation scheme, Y_p and Y_w were simulated with the crop growth simulation model WOFOST version 7.1.3 (release March 2011) (Wolf et al., 2011; Supit et al., 2012), for maize in the U.S., winter wheat in Germany, and sorghum in Western Africa. Per climate zone crop management and soil data were kept constant. The variation in simulated Y_p and Y_w among RWSs located within the same climate zone served as a measure of the performance of the climate zonation scheme for upscaling of Y_p and Y_w.

3.2.1. Input data description

Weather data for the U.S. originated from the National Oceanic and Atmospheric Association (NOAA), and Global Summary of the Day (GSOD). Stations were only selected when they were located in climate zones with ≥10,000 ha of rainfed maize (using the SPAM2000 database; You et al., 2006, 2009). Weather data for Germany originated from the German Meteorological Service (Deutscher Wetterdienst). Only stations with publically available data were utilized. In addition, for both the U.S. and Germany, only stations that had sufficient data available in the period 1997–2011 were selected (i.e. per year no more than 20 consecutive days and 10% of the days could be missing for each important weather variable). Missing data were substituted using linear interpolation between available dates. Weather data for Western Africa were collected within the Global Yield Gap Atlas project and originated from national meteorological services complemented with propagated data, i.e. gridded weather data corrected with help of a few years of measured weather data (see Van Wart et al., 2015; Grassini et al., 2015). Data from the period 1998–2007 were used. For all three countries/regions incident solar radiation was obtained from NASA POWER agro climatology solar radiation data, which were available on a 1° × 1° global grid (Stackhouse, 2014; http://power.larc.nasa.gov/).

Per climate zone the most prevailing soil type with respect to harvested area of the crop of interest, was selected from the global gridded ISRIC-WISE soil database. One representative crop emergence date and the dominant cultivar were selected per climate zone for simulation of Y_p and Y_w. Crop management data for maize in the U.S. were allocated to the stations based on the geographical location of the stations. For stations with a latitude <37° the emergence date was estimated to be at day of year (DOY) 60, for stations with latitudes between 37° and 42° at DOY 91, for stations with latitudes >42° at DOY 121. Based on the emergence day temperature sum requirements were allocated to the stations, giving stations with emergence days at DOY 60 the largest and stations with emergence days at DOY 121 the smallest temperature requirements. When a climate zone crossed the latitude thresholds, per climate zone the dominant emergence dates and temperature requirements were selected. Crop management data for Western Africa and Germany originated from country experts; again per climate zone the dominant cultivar temperature sum requirements and emergence dates were selected.

3.2.2. Comparison of simulated yields within climate zones

To assess the degree of agreement between the simulated yields within a climate zone, first the simulated long-term average yield was calculated for each RWS. Next the coefficient of variation (CV, %) was calculated per climate zone:

$$\mathrm{CV} = \frac{\sigma_{\mathrm{cz}}}{\mu_{\mathrm{cz}}} \times 100\% \quad (7)$$

with σ_{cz} the standard deviation and μ_{cz} the average of the long-term average yields across RWSs located within the same climate zone.

4. Results: Performance of the Global Yield Gap Atlas upscaling protocol

4.1. Application and spatial coverage

4.1.1. Sensitivity of the estimated national $\mathrm{Y_w}$ to harvested area covered

Estimates of Y_w at a national level for maize changed little after reaching the threshold of 50% coverage of the national harvested area by the RWS buffer zones for the four tested countries (Burkina Faso, Ghana, Uganda, and Kenya) (Fig. 3). For Burkina Faso the national Y_w estimate was even robust (i.e. at most a deviation of 5% of the national Y_w estimate based on all RWS buffer zones) after reaching 16% coverage. The required coverage for robust Y_w estimates for Ghana, Uganda and Kenya was 49%, 52% and 44%, respectively.

By randomly selecting Y_w estimates at the RWS level until at least 25% of the national harvested area was covered, a situation could be mimicked in which RWS buffer zones were selected with smaller harvested area coverage and a smaller total coverage of the harvested area was reached. Area-weighted national Y_w estimates were calculated for each selection. In comparison to national Y_w estimates based on the recommended coverage (approximately 50%), the national Y_w's based on less coverage were under- or overestimated with at most 3% in Burkina Faso, 5% in Ghana, 10% in Uganda, and 27% in Kenya. The results showed that the possible error in Y_w at the national level due to a small coverage of national harvested area was greatest in countries with a large range in simulated Y_w (Fig. 3, range in red triangles, e.g. Kenya).

4.1.2. Burkina Faso and Ethiopia as case studies

To illustrate the applicability of the described protocol, results for water-limited sorghum for two countries, contrasting with respect to topography, are described in detail: Burkina Faso (Table 1) and Ethiopia (Table 2).

For the sorghum simulations in Burkina Faso ten RWSs, located in four climate zones, were used for the Y_g analysis (Table 1). Each of these RWS buffer zones included at least 4.4% of the national harvested area of rainfed sorghum in Burkina Faso and in total 73% of the national harvested area was covered. The associated climate zones covered 96% of national harvested sorghum area. The Y_w at the country level showed a spatial variability (expressed as CV, based on the long-term simulated Y_w at RWS level) of 27%.

In Ethiopia, 24 RWSs were used for sorghum simulations, located in 16 climate zones (Table 2). A significant part of the selected RWSs (10 out of 24) covered >1% of the national harvested rainfed sorghum area in Ethiopia. In total 27% of the national harvested area was included in these RWS buffer zones. The associated climate zones covered 64% of the national harvested area. The Y_w at country level showed a spatial variability (expressed as CV, based on the long-term simulated Y_w at RWS level) of 39%.

4.1.3. Coverage achieved following the protocol: Western versus Eastern Africa

Coverage of national harvested area by selected RWSs in each country (Table 3) and associated climate zones (Table 4) for eight additional countries in Sub-Saharan Africa displayed the same trend, as observed for Burkina Faso and Ethiopia (Tables 1 and 2). In Western Africa cereal growing areas, a region with relatively homogenous topography, only 13% of the country-crop combinations had one or more RWS buffer zones with <1% of the national harvested area selected by the protocol for simulation of Y_w. By contrast, in Eastern Africa, a region with a more heterogeneous topography, 76% of selected RWS included <1% of national sorghum area (Table 3).

In Western Africa, the selected RWS buffer zones covered at least 50% of the national harvested area in 12 of 23 country-crop combinations versus 5 out of 21 country-crop combinations for East Africa (Table 3). Despite the difference in coverage by RWS buffer zones in Western and Eastern Africa, total coverage of national harvested area by the selected climate zones was remarkably similar between Western and Eastern Africa, on average 78% and 62%, respectively (Table 4), and thus much larger than coverage by RWS buffer zones, which highlights the importance of climate zone performance as assessed in Section 4.2.

4.2. Performance of the climate zonation scheme

To test the assumption that weather data from a selected station are representative for the climate zone in which it is located, 28 zones in the U.S., and eight zones in both Germany and Western Africa with at least three RWSs (Table 5) were selected.

Overall, agreement in simulated Y_p among stations located in the same climate zone was large in all three studied countries/regions (agreement expressed as CV, Eq. (7), Fig. 4a, Table 5). In general, for all three countries/regions the most important climate zones with respect to harvested crop area, showed the smallest CV. Discrepancies were only large for a few zones, which often had small production areas (<1%) and large topographical variation and are less suitable for crop production, e.g. the zones in Germany with CV >30%.

For all countries/regions the area-weighted CV of the simulated Y_w was greater than the CV of Y_p (Table 5). In the U.S. and Western Africa clear spatial trends in the CV of Y_w were visible (Fig. 4b): in Western Africa the CV increased towards the north, and in the U.S. it increased towards the west which are both relatively harsh crop production environments due to relatively large aridity values.

5. Discussion

5.1. Performance of the Global Yield Gap Atlas upscaling protocol

In general, our bottom-up protocol for yield gap estimation was more applicable, in terms of compliance with the defined criteria (≥50% coverage of the national harvested area), in countries with less topographic heterogeneity (e.g. in Western Africa). Less topographic heterogeneity resulted in larger climate zones and consequently, clipping of RWS buffer zone borders by climate zones was less frequent, which resulted in larger harvested area per buffer

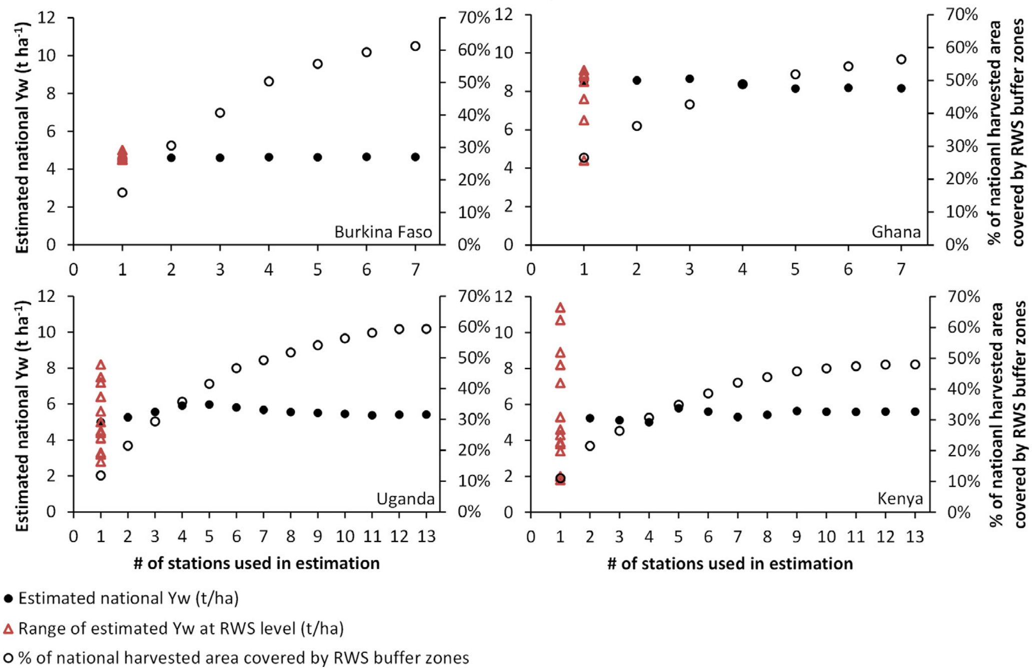

Fig. 3. Estimated national Y_w for maize as influenced by the number of used RWS (solid black circles) and associated percentage of harvested total crop area used to simulate Y_w (open circles). Range of simulated Y_w at all RWSs are shown by the open red triangles.

zone. In countries with strong topographic heterogeneity and large altitude ranges (mainly in Eastern Africa), climate zones were considerably smaller and it was more difficult to identify a RWS in each climate zone that was representative for the crop and country of interest. To make full use of the available weather data in such countries, weather stations were also selected in climate zones where the crop is not or hardly grown according to SPAM2000.

After consultation with local experts, we concluded that the SPAM2000 maps (spatially disaggregated distribution of crops averaged for years around 2000) may be obsolete with regards to the current distribution of harvested area for many of the studied crops. For example, in Eastern Africa the harvested area of maize has increased by 50% between 2000 and 2013, and in Western Africa by 75% (FAOSTAT, 2014). These changes in crop area and likely also distribution, explain to some degree why it was not possible to comply with the crop area coverage criterion for all country-crop combinations, as crop management data, required to run the models, could not be collected in regions where the crop is no longer grown (e.g. sorghum or millet replaced by maize). Moreover, the consulted experts provided additional management data, valid for regions that were not selected based on the SPAM2000 maps but are currently important growing areas. Following the recommendations of these local experts, Y_p and Y_w were also simulated for these additional regions. To include these yield estimates in the scaled up yield estimates SPAM2000 harvested area was used, due to lack of more recent quantitative information on crop harvested areas, leading to an underestimation of the importance of these regions in scaling up. Possible errors in national yield potentials due to inaccurate land use maps were shown before by Folberth et al. (2012), who found that a crop area map that was too coarse with regard to where irrigated and rainfed maize is grown in the U.S., resulted in inaccurate yield estimates at national scale. Like others (e.g. See et al., 2015), we therefore stress the importance of continuous updating and improving crop distribution maps such as SPAM2000 in order to increase the accuracy of Y_g at large spatial scales.

The analysis to assess the performance of the selected climate zonation scheme showed that the CV of simulated Y_p resulting from RWSs located within the same climate zone is small. In environments with favourable rainfall patterns for crop growth, such as the southern parts of Western Africa, CV of simulated Y_w was also small. By contrast, in semi-arid areas (e.g. central parts of the U.S. and northern parts of Western Africa, representing aridity limits of production for a given crop species and with large variability in rainfall), the CV of simulated Y_w was rather large (approximately

Table 1
Water-limited sorghum yields and coverage of the national harvested area in Burkina Faso per reference weather stations (RWS) selected by the upscaling protocol.

RWS	% Coverage of national harvested area by buffer zone	% Coverage of national harvested area by climate zone	Y_w (t ha^{-1})		
			RWS	Climate zone	Country
Bogandé	8.4	39.1	4.4	4.3	4.8
Ouahigouya	9.7		4.3		
Boromo	8.6	34.6	5.3	5.3	
Dédougou	9.0		5.5		
Fada Ngourma	8.7		4.6		
Pô	8.0		6.1		
Dori	5.1	11.6	3.0	3.5	
Hypothetical station 1	5.4		3.9		
Bobo-Dioulasso	4.4	11.2	7.7	6.5	
Gaoua	5.5		5.5		
National total	73	96			

Table 2
Water-limited sorghum yields and coverage of the national harvested area in Ethiopia per reference weather stations (RWS) selected by the upscaling protocol.

RWS	% Coverage of national harvested area by buffer zone	% Coverage of national harvested area by climate zone	Y_w (t ha^{-1})		
			RWS	Climate zone	Country
Dire Dawa	3.0	13.41	3.0	5.6	6.0
Harar	3.1		8.3		
Kobo	0.1		2.8		
Melkassa	0.8		5.2		
Shire Endasilasse	3.8		5.5		
Hypothetical station 1	3.5		5.6		
Jijiga	0.4	10.72	2.3	2.3	
Assosa	1.5	7.09	7.9	7.4	
Gondar	0.2		4.1		
Kombolacha	0.1	5.29	3.9	8.1	
Woliso	0.9		9.7		
Wolkite	1.1		7.4		
Hypothetical station 2	0.6	5.00	5.9	5.9	
Ambo	1.3	4.26	7.5	7.5	
Gelemso	1.4	3.83	8.5	8.5	
Haramaya	1.2	2.91	8.0	8.0	
Nekemte	0.9	2.68	6.3	6.3	
Bahir Dar	0.0	2.33	5.1	5.1	
Mekele	1.4	1.84	2.6	2.6	
Ayira	0.8	1.68	8.1	8.1	
Butajira	0.5	1.34	6.0	6.0	
Gore	0.2	1.28	9.6	9.6	
Pawe	0.2	0.25	5.3	5.3	
Shambu	0.1	0.20	10.2	10.2	
National total	27%	64%			

Table 3
Percentage of national harvested area covered by buffer zones of the selected RWS in ten African countries, when following the protocol as much as possible. In parentheses the percentage of selected RWS that cover <1% of national harvested area, blank cells indicate that this country/crop combination had less than 100,000 ha (criteria to be simulated).

Country/crop	Rainfed maize (%)	Rainfed wheat (%)	Rainfed sorghum (%)	Rainfed millet (%)	Rainfed rice (%)	Irrigated rice (%)
Mali	35 (0)		35 (13)	51 (38)	57 (0)	59 (0)
Niger			54 (0)	51 (0)		17 (0)
Burkina Faso	61 (0)		73 (0)	75 (0)	48 (0)	59 (0)
Nigeria	27 (44)		39 (0)	34 (0)	25 (0)	25 (0)
Ghana	56 (0)		74 (0)	75 (0)	40 (0)	22 (0)
Ethiopia	22 (68)	26 (25)	27 (64)	26 (65)		
Kenya	49 (29)	28 (43)	31 (67)	27 (50)		
Uganda	61 (7)		65 (18)	68 (9)	53 (33)	
Tanzania	30 (44)	44 (0)	45 (0)	55 (9)	16 (0)	13 (0)
Zambia	26 (55)			18 (57)	34 (0)	

Table 4
Percentage of national harvested area covered by the selected climate zones in ten African countries when following the protocol as much as possible. In parentheses the percentage of selected climate zones that cover <5% of national harvested area, blank cells indicate that this country/crop combination had less than 100,000 ha (criteria to be simulated).

Country/crop	Rainfed maize (%)	Rainfed wheat (%)	Rainfed sorghum (%)	Rainfed millet (%)	Rainfed rice (%)	Irrigated rice (%)
Mali	59 (0)		81 (25)	96 (25)	83 (0)	84 (0)
Niger			97 (0)	94 (0)		71 (50)
Burkina Faso	75 (0)		96 (0)	99 (0)	65 (0)	90 (0)
Nigeria	65 (50)		78 (22)	79 (38)	46 (17)	53 (17)
Ghana	87 (0)		90 (0)	90 (0)	55 (0)	57 (0)
Ethiopia	58 (64)	52 (44)	64 (75)	45 (83)		
Kenya	56 (60)	36 (50)	53 (60)	49 (50)		
Uganda	77 (14)		74 (14)	76 (0)	78 (0)	
Tanzania	72 (29)	51 (25)	74 (20)	78 (0)	41 (50)	37 (0)
Zambia	85 (20)			90 (0)	50 (0)	

Table 5
Number of selected climate zones, number of selected RWS per climate zone, and the area-weighted CV (among RWS) for Y_p and Y_w within each zone.

Country/region and crop	Number of selected climate zones	Number of RWS			Area-weighted CV (%)	
		Average per climate zone	Minimum in a zone	Maximum in a zone	Y_p	Y_w
U.S.—maize	28	6.8	3	25	5	19
Germany—winter wheat	8	5.6	3	8	4	8
Western Africa—sorghum	8	7.8	3	21	7	23

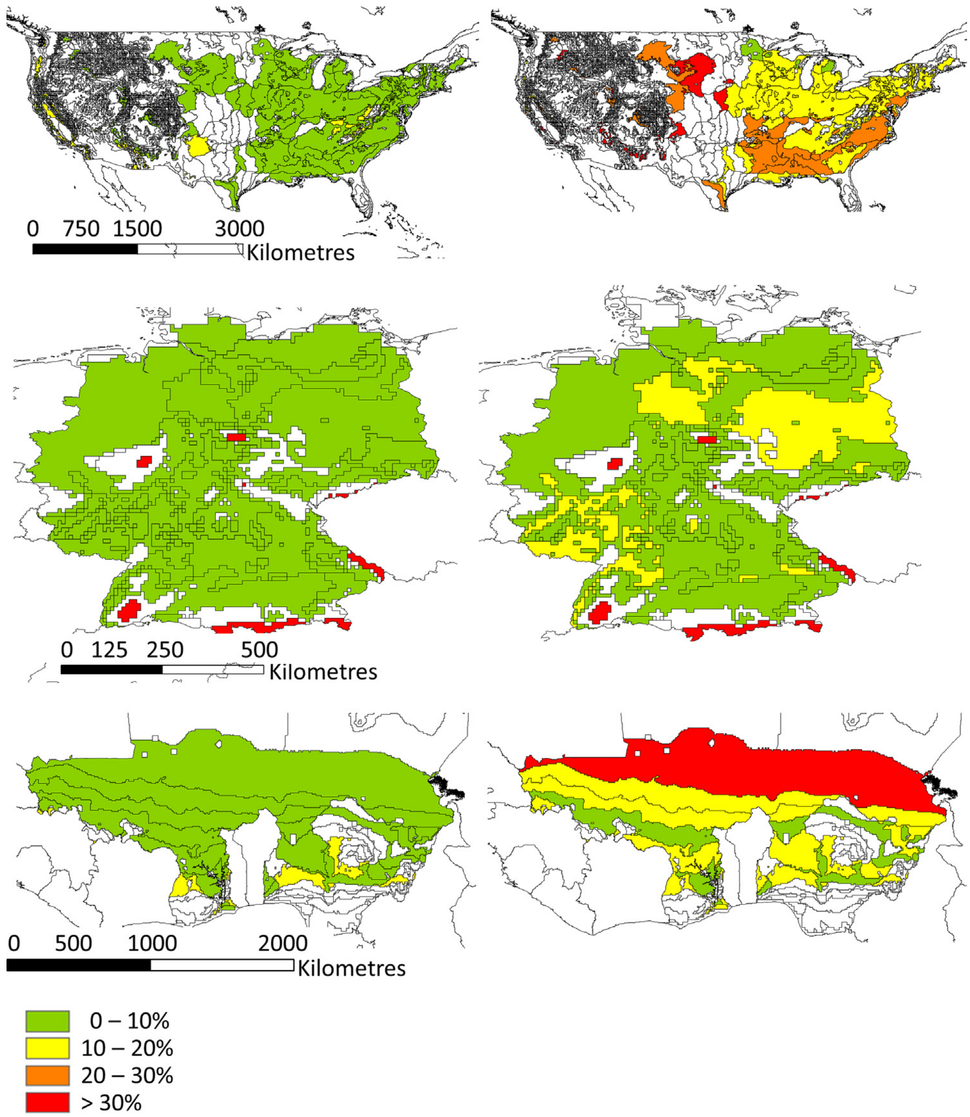

Fig. 4. CV for (left to right) simulated Y_p and simulated Y_w of RWSs located within the same climate zone, for (top to bottom): U.S. (maize), Germany (wheat), and Western Africa (sorghum).

35%). These results show that the climate zonation scheme used in the protocol is effective for scaling up Y_g estimates at RWS level to larger spatial scales with sufficient precision under most climate conditions. The semi-arid areas are an exception and Y_g estimates can here be prone to errors, especially if only a limited number of weather stations is available per climate zone. In line with Thornton et al. (2014) we therefore stress the importance of strengthen initiatives to publically unlock rainfall data and increase the number of weather stations with publicly available data.

To our knowledge no other studies exist that evaluated the performance of a climate zonation scheme as the basis for scaling up location-specific crop growth simulation results. Yet recent studies, such as Nendel et al. (2013) and Zhao et al. (2015), have noted the errors introduced when crop growth models are used with a top-down approach that applies using input data at large spatial scales. Due to differences in the studied regions with respect to climatic conditions and applied methodologies, the value of direct comparisons with our study is limited. Consistent with our findings, however, Zhao et al. (2015) concluded that weather data with high resolution should be used in regions with large spatial heterogeneity in weather data, which is a characteristic of the semi-arid climate zones. Likewise, Nendel et al. (2013) concluded that crop yields for a given region could be considerably underestimated if spatial distribution of available weather data is poor for the area under investigation.

5.2. Spatial coverage

Our evaluation of effect of the spatial coverage of the national harvested area by the RWS buffer zones on the estimated national Y_w showed that the threshold of 50% coverage resulted in robust maize Y_w estimates at national scale. These results are in close agreement to the findings of Van Wart et al. (2013b). In countries in which a small range in Y_w at RWS level was simulated (e.g. Burkina Faso), coverage of 20% was sufficient to achieve a robust maize Y_w estimate at the national level. For approximately 40% of the simulated country-crop combinations, at least 50% of the national harvested area was covered by the RWS buffer zones, which thus resulted in robust estimates of national Y_w for these country-crop combinations. Due to missing data and inaccuracy of the harvested crop area maps, a smaller coverage was attained for the other country-crop combinations. However, for the large majority of the country-crop combinations not reaching the 50% coverage, we were still able to cover at least 25% of the national harvested area (20 out of 27). A coverage of only 25% could introduce some errors in the scaled up Y_w estimates, especially for countries in which the Y_w estimates at RWS level show a large range (e.g. maize in Kenya, Fig. 3). However, the magnitude of that error was limited for maize to 1 t ha^{-1} for 3 out of the 4 studied countries. When considering the coverage by climate zones, only for 5 out of 44 country-crop combinations a coverage of less than 50% was attained. In combination with the demonstrated robustness of the climate zonation, we conclude that in general the scaled-up Y_g estimates at national level are sufficiently accurate.

Recent research showed the uncertainty in global gridded crop models for climate change impacts on agriculture (Rosenzweig et al., 2014). The authors indicated this uncertainty was mainly due to differences in structure and implementation of the applied crop models and assumptions made about agricultural management, e.g. input quantities. Uncertainties related to their applied scaling methods, in which site-based crop models were run with global gridded weather data, were not quantified nor discussed. The current study could quantify the error and uncertainty in the national scale results from the applied scaling methods. Hence, the upscaling approach and analysis developed and described here could help quantify such uncertainty for large-scale crop model studies.

To increase understanding about spatial variability within climate zones and scaled up Y_g estimates based on the bottom-up approach described in this paper, future work should focus on variability in soil properties, especially properties influencing soil water holding capacity and rooting depth, and their effects on upscaled Y_g estimates. The issue of examining rainfall data characteristics and effects of different rainfall data quality on results also needs to be studied. Finally, increased efforts to collect and make publicly available good quality weather, soil, and crop management data in regions with substantial harvested area that lack these data would have large payoffs for improving quality of yield gap estimates in SSA.

6. Concluding remarks

This study shows that the proposed protocol developed and applied in the Global Yield Gap Atlas project is reasonably robust for scaling up Y_g estimates to regional and national levels based on weather station data supplemented by local soil and cropping system data. This conclusion was based on an evaluation of the climate zonation scheme, which appeared to be accurate enough to achieve robust Y_g estimates at larger spatial areas and sufficient coverage of harvested crop area by the protocols for selecting weather stations. Semi-arid areas with large variability in rainfall are an exception and here scaled up water-limited yield gap estimates can be prone to errors, especially if only a limited number of weather stations is available per climate zone. In addition, in some heterogeneous countries data availability hindered full application of the protocol, leading to possible errors in the scaled up yield gap estimates.

We found that global crop area distribution maps are still a source of error for selecting relevant locations for data collection for Y_g estimates. Continuous updating and improving of crop distribution maps is essential, and should be complemented with local up-to-date knowledge about crop area distribution.

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