Field Crops Research 267 (2021) 108160

Contents lists available at ScienceDirect

Field Crops Research

journal homepage: www.elsevier.com/locate/fcr

Environmental characterization and yield gap analysis to tackle genotype-by-environment-by-management interactions and map region-specific agronomic and breeding targets in groundnut

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ARTICLE INFO

Keywords:
Homogeneous production units
Potential yield
SSM model
Crop design
Target population of environment

ABSTRACT

The high degree of Genotype by Environment by Management (GxExM) interactions is a serious challenge for production and crop improvement efforts. This challenge is especially true for a crop like groundnut that is often grown as a rainfed crop in diverse environments and management, leading to considerable production fluctuations among regions and seasons. Developing a means to characterize the drivers of variable yield and to identify region specific breeding objectives were the main motivations for this research, using groundnut production in India, as a case study for rainfed crops. Historically, five groundnut production areas have been considered by Indian crop improvement programs. Our objectives were to assess the relevance of this zonation system and possibly to re-define production areas with a higher degree of similarities into homogeneous production units (HPUs). Towards this, we used yield gap analysis and the geo-biophysical characters of the production region to understand and deal with GxExM interactions. Weather and soil data, crop parameters, and management information data were collected and groundnut production was simulated at the district scale over 30 consecutive years. Consequently, the geographic distribution of the potential yields and the yield gaps were first estimated to understand the main production limitations in a given region. Large and variable yield gaps (with a mean of ~70 %) were observed and results revealed a readily exploitable production gap (~ 8 M tons), which might be bridged by following recommended agronomic practices. Water deficit limited the yield potential by an average of 40 %, although with large variability among districts. However, large and variable yield gaps remained. To resolve the unexplained variation, principal component and cluster analysis of agronomic model output together with geo-biophysical indicators for each district were carried out. This resulted in seven HPUs, having well-defined production-limiting constraints. Grouping by HPU greatly reduced variance in actual and simulated yields, as compared to grouping across all groundnut production zones in India. The HPU based approach delimited precise geographic regions within which HPU-specific GxM products could be designed by crop improvement programs to boost productivity.

1. Introduction

Sustainable food production for a rising population of ca. 9.7 billion people by 2050 (UN, 2019, medium variant), is a major concern directly involved in several globally defined sustainable development goals (#1, #2, #12). However, yield trends are far below what is needed to meet the projected demands (Fischer et al., 2014; Ray et al., 2013) and resource constraints for agricultural production have become more stringent than in the past while the growth of yields is slowing down (Alexandratos and Bruinsma, 2012) or almost ceased in some environments (Brisson et al., 2010; Lin and Huybers, 2012). Then, achieving sustainable food security needs both to accelerate rates of yield

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https://doi.org/10.1016/j.fcr.2021.108160
Received 6 October 2020; Received in revised form 2 April 2021; Accepted 15 April 2021
Available online 28 April 2021

improvement (Voss-Fels et al., 2019) and to reduce on-farm yield gaps (Fischer et al., 2014).

While presence of Genotype by Environment by Management (GxExM) interactions complicates the identification of desirable crop design (GxM combinations) (Hammer et al., 2014), it creates opportunities for new crop improvement strategies (Cooper et al., 2020). Breeders focus mostly on high yield heritability (Chenu, 2015), but heritability declines as interactions of GxExM increase, and this constrains the selection of germplasm with consistent performance across environments (Hammer et al., 2014). Understanding and quantifying the causes of such interactions are critical to develop GxM packages that maximize production in specific environmental circumstance (Chauhan and Rachaputi, 2014; George, 2014). Yet, this remains a major knowledge gap in most breeding programs (Cooper et al., 2020), where significant GxExM interactions hamper the crop improvement progress (Chenu et al., 2011). Such interactions have been reported for groundnut in situations varying in water regimes (Hamidou et al., 2012) or combination of water regimes and heat stress (Hamidou et al., 2013). A GxExM analysis permits a nuanced understanding of the factor(s) that lie behind regional differences in the yield gaps (Porter et al., 2010), and this is done regularly with multi-environment trials (METs). However, METs are generally restricted by the number and the location of trial sites (Ramirez-Villegas et al., 2020; Witcombe et al., 1998) and number of seasons (Chenu, 2015), which limits the spatio-temporal reach of the GxExM analysis (Kholová et al., 2020). In contrast, an *in-silico* analysis via crop simulation modeling can help us overcome these spatial and temporal limitations (Cooper et al., 2020; Heinemann et al., 2015; Ramirez-Villegas et al., 2020).

Various approaches allow to classify the crop production regions for breeding purposes within the concept of target populations of environments (TPE; Comstock, 1977). Yield-based methods have been in use for decades to reduce GxE interaction (Cooper and Woodruff, 1993). The concept of mega-environments (MEs, Rajaram et al., 1994) developed by CIMMYT to target wheat germplasm development has used similarities in environmental variables and cropping system requirements to cluster regions. Crop simulations have also been used to successfully characterize TPEs as they can classify stress patterns with regards to frequency or intensity within a geographical space (e.g. Battisti and Sentelhas, 2019; Chapman et al., 2000; Chauhan and Rachaputi, 2014; Chenu et al., 2011; Cooper et al., 1997; Hajjarpoor et al., 2018b; Heinemann et al., 2015; Kholová et al., 2013; Sciarresi et al., 2019). Here, we hypothesize that a yield gap analysis using crop simulation (including the estimation of non-water limited potential yield, water-limited potential yield, and the gap between actual and potential yield), combined with the analysis of soil and environmental factors, could help divide the entire production area into sub-units reflecting potential production and environmental constraint, within which the degree of GxExM interactions would be smaller. This approach would also provide a quantitative estimate to compare the food production capacity for a given area with the actual production (van Wart et al., 2013a). It would then offers a critical basis for crop improvement programs at regional, national and global scale (Chauhan and Rachaputi, 2014; George, 2014; Hajjarpoor et al., 2018a, 2018b; Pradhan et al., 2015; Soltani et al., 2016; Vadez et al., 2017).

Groundnut cultivation in India primarily relies on rainfed agricultural practices and yields fluctuate vastly by season and region (Rathnakumar et al., 2013). Since the establishment of All India Coordinated Research Project (AICRP) in 1967 and subsequently, with the establishment of a separate project for groundnut (AICRP-Groundnut) in 1992, groundnut growing areas in India have been divided into five production zones. This zonation was based on a few criteria (Rathnakumar et al., 2013), like the length of the growing period across all locations, which has changed by now in many locations (Mausch and Bantilan, 2012). In relation to this, Witcombe et al. (1998) discussed the problem that experimental stations (AICRP centers) were not located in the main production areas and argued for an increasing the number of zones in pearl millet, sorghum, chickpea, and groundnut. Some work has characterized Indian crop production systems for post-rainy sorghum (Kholová et al., 2013 and Ronaki et al. under review) and post-rainy chickpea (Hajjarpoor et al., 2018b) and showed the need for an update on traditional zonation. This is our hypothesis regarding the classical zonation of groundnut production in India.

Therefore, the overall objective was to study the groundnut production areas in India to assess the validity of the classical zonation and possibly to re-define these production environments into homogeneous production units (HPUs) with a higher degree of similarities in order to guide crop improvement programs through GxExM complexities. Specifically, we intended to i) analyze the main production limitations using yield gap approach to map and dissect the reasons for groundnut yield variability in India, ii) classify the major production districts into HPUs based on similarities found in the yield gap analysis together with geo-biophysical indicators, and iii) test whether the variation in GxExM interactions, proxied by a coefficient of variation among districts of a given HPU, is reduced by comparing across years and districts within each HPU rather than in the entire groundnut production area.

2. Materials and methods

2.1. Overview

A modeling approach was used to quantify region-specific constraints and the yield gaps limiting groundnut productivity in India. The main production areas were identified utilizing official source of district-level information on agricultural production and satellite imagery. The basic information on district variability in soil properties, local agronomic practices and preferred cultivars were gathered by personal communication with national centers dealing with groundnut crop improvement. To compensate for erratic coverage and low quality of observed weather information across the focus area, we utilized 30 years of gridded weather data as a substitute. The SSM-iLegume model was used to simulate groundnut productivity across the major groundnut producing districts. The outputs of the model have been used to calculate the district-wise production potential, water-deficit index and the associated yield gap. Finally, the observed geo-biophysical properties of the districts and the simulation results of yield gap analysis were used in a combined analysis to cluster groundnut-growing districts into units with higher degrees of similarities; i.e. homogeneous production units (HPUs).

2.2. Definition of target groundnut production area

Time-series of district-level groundnut cultivated area (ha/district), production (kg/district), yield (kg ha^{-1}) across the three cultivation seasons (rainy, post-rainy, summer season) were obtained from the District Level Database (DLD) web tool (http://data.icrisat.org/dld/index.html) developed for Indian agriculture and allied sectors. Fifteen years of data from 2001 to 2015 were considered to capture the seasonal variability in groundnut production. This time frame data was considered sufficient to account for year-to-year variability in actual yield due to weather, especially in harsh rainfed environments (Grassini et al., 2015) while avoiding the bias due to the previous technological time-trend (van Ittersum et al., 2013). As 82 % of groundnut was found to be cultivated in the rainy season ("Kharif"), that season was the focus of the simulation study. A selection of the districts encompassing 80 % of the production area was used to define the main groundnut production tract in India. In addition, the districts identified by satellite imagery during the rainy season of 2013–2014 (http://maps.icrisat.org/rs/maps/index.html) as well as districts showing an increasing trend in groundnut cultivation area (i.e., minimum 1000 ha of cultivated area increase between 2011–2015) were added to the main groundnut production tract to be analyzed in the study. The information on the proportion and mode of the irrigated area during the rainy season was obtained from ICAR-Central Research Institute for Dryland Agriculture (Raju et al., 2018).

2.3. Model set-up and simulations

2.3.1. Model description and evaluation

To simulate groundnut growth, development and yield formation, the SSM-iLegume model of Soltani and Sinclair, 2012, 2011) was used. This model is a simple mechanistic model that is suited for geospatial assessment according to specific requirements (see Sinclair et al., 2020; van Ittersum et al., 2013). It has also been shown to be highly reliable in studies encompassing the wide range of environments for various legume species including chickpea (Hajjarpoor et al., 2018b; Soltani and Sinclair, 2011; Vadez et al., 2013, 2012), soybean (Sinclair et al., 2014), bean (Marrou et al., 2014), lentil (Ghanem et al., 2015) and groundnut (Vadez et al., 2016, 2017). The model uses daily time steps to arbitrate crop, weather and soil information and has the flexibility to simulate management practices like sowing date and planting density.

All the genotype-specific coefficients required by the model were calculated from published results describing the development, growth, and yield of groundnut (Halilou et al., 2016; Singh et al., 2012; Vadez et al., 2017, 2016). The parameters required to define the crop were those of standard Spanish-type and Virginia-type cultivars. To check the robustness of the model under typical cultivation conditions in India, linear regression function was fitted on pod yield data predicted by model vs measured in 25 trials across India (Table 1).

2.3.2. Soil data

Gridded soil data at a spatial resolution of 250 m are available for India (www.isric.org) included only generic soil profiles that did not sufficiently represent the district-wise groundnut. Rather than using gridded soil data, we chose to collect information on common soil types and effective rooting depths typical for groundnut production of each district by consulting the local experts (details in Table 2). We ran the model for all types of soil if we received different information from expert consultation.

2.3.3. Weather data

A major limitation in attempting relevant simulations across a wide geographical area was assembling a weather database of sufficient geographical resolution (Mourtzinis et al., 2017; Vadez et al., 2017; Van Wart et al., 2015). This is also the case of India as there is a general lack of quality weather information (Hajjarpoor et al., 2018b), further complicated by the fact that the databases are not open-source (http://dsp.imdpune.gov.in/). A possible surrogate for regions where weather station network is irregular is the use of gridded weather data (GWD). For that purpose, several sets of GWD were tested for its suitability for this research exercise (i.e., IMD (Indian meteorological department), AgMERRA (both 0.5°x0.5° and 1°x1° resolution, Ruane et al. (2015)), NASAPOWER (https://power.larc.nasa.gov/) and MarkSim (Jones et al., 2002; Jones and Thornton, 2000) by comparing them to available observed weather data (24 weather stations; Tmin, Tmax, rainfall quantity and distribution). This is crucial because, when generating long-term weather data with global spatial coverage, sources of error can be incorporated into synthetic data that can result in a degree of uncertainty when estimating crop yield and its variability over time (Mourtzinis et al., 2017; Van Wart et al., 2015). The correlation coefficient and normalized root mean square of error ($RMSE_n$) were computed to evaluate the degree of agreement between these weather data sources. As each GWD predicted some parameters better than others, final test of met-data suitability was done by comparison of groundnut yield and biomass simulated using GWD sources against observed weather

Table 2
The range of soil characteristics used for simulations.

Character	Condition
Volumetric extractable Water Content (VWC)	0.09 to 0.13 cm cm^{-1}
Soil lower limit (LL)	0.16 to 0.25 cm cm^{-1}
Soil saturation limit (SAT)	0.40 to 0.45 cm cm^{-1}
Soil drained upper limit (DUL)	0.25 to 0.38 cm cm^{-1}
Soil albedo	0.13 to 0.14
Curve number*	73 to 82
Soil depth	60 to 120 cm
Initial soil nitrogen	2 g N m^{-2}

* Daily runoff (RUNOF, mm) is calculated using a simplified curve number procedure developed by scientists at USDA-Soil Conservation Service (SCS). In the curve number method, daily surface runoff is calculated as a function of daily rainfall (RAIN, mm) and a soil retention parameter (From Soltani and Sinclair, 2012).

Table 1
Experimental trials used for model evaluation.

Location	Latitude	Year	Sowing date	Season	Treatment[a]	Ref
ICRISAT	17.8	2008–09	10-December	Post-rainy	ws	Vadez et al. (2016)
ICRISAT	17.8	2008–09	10- December	Post-rainy	ww	Vadez et al. (2016)
ICRISAT	17.8	2009–10	12- December	Post-rainy	ws	Vadez et al. (2016)
ICRISAT	17.8	2009–10	12- December	Post-rainy	ww	Vadez et al. (2016)
ICRISAT	17.8	2010–11	8- December	Post-rainy	ws	Vadez et al. (2016)
ICRISAT	17.8	2010–11	8- December	Post-rainy	ww	Vadez et al. (2016)
ICRISAT	17.5	2011	28-July	Rainy	ww	HLOGVT trial
ICRISAT	17.8	2011–12	16- December	Post-rainy	ws	Vadez et al. (2016)
ICRISAT	17.8	2011–12	16- December	Post-rainy	ww	Vadez et al. (2016)
ICRISAT	17.5	2012	4- July	Rainy	ww	HLOGVT trial
Junagadh Univ.	21.5	2012	7-June	Rainy	ws	HLOGVT trial
DGR, Junagadh	21.4	2012	30-June	Rainy	ws	HLOGVT trial
ICRISAT	17.5	2012	4- July	Rainy	ws	HLOGVT trial
ICRISAT	17.5	2012–13	12- December	Post-rainy	ws	HLOGVT trial
ICRISAT	17.5	2012–13	12- December	Post-rainy	ww	HLOGVT trial
ICRISAT	17.8	2012–13	12- December	Post-rainy	ws	Unpublished data
ICRISAT	17.8	2012–13	13- December	Post-rainy	ww	Unpublished data
ICRISAT	17.8	2012–13	13- December	Post-rainy	ws	Vadez et al. (2016)
ICRISAT	17.8	2012–13	13- December	Post-rainy	ww	Vadez et al. (2016)
DGR, Junagadh	21.4	2013	29-January	Post-rainy	ww	HLOGVT trial
DGR, Junagadh	21.4	2013	28- January	Post-rainy	ws	HLOGVT trial
ICRISAT	17.8	2013–14	15- December	Post-rainy	ws	Vadez et al. (2016)
ICRISAT	17.8	2013–14	15- December	Post-rainy	ww	Vadez et al. (2016)
ICRISAT	17.8	2014	20-August	Rainy	ws	Unpublished data
ICRISAT	17.8	2014	21-August	Rainy	ww	Unpublished data

[a] ws, water stress; ww, well-watered.

information (Suppl. Fig. S1). Hajjarpoor et al. (2018b) used the same approach to avoid restrictions imposed by limited weather data in a simulation study of chickpea across India. However, each data source has some advantages and disadvantages according to the area and parameters (Van Wart et al., 2015). As the yield predictions based on observed weather information were the most correlated to the simulation that used AgMERRA 0.5°x0.5° data (RMSE = 55 g m^{-2}, $RMSE_n$ = 17 %), the modeling analysis of this study was conducted with this GWD.

2.3.4. Management

In the simulations, a sowing density of 33 plants m^{-2} was used, as per the recommended practices for groundnut cultivation in India (Annual Report, 2015-16). Being capable of fixing atmospheric nitrogen through rhizobial symbiosis, groundnut crop requires only a small amount of basal N application for establishment prior to the formation of nodules. This requirement was accounted for in simulations by reflecting the recommended basal fertilizer dose of 2 g N m^{-2} (Trivedi, 2009) as the initial soil nitrogen content. A district-specific sowing date was set for the first date in the rainy season determined sowing window. The sowing windows, which were taken from expert consultation, varied between 10–80 days. The earliest sowing window starts on 1st May in the North (in Rajasthan) and the latest 1st July in the South (in Andhra Pradesh). The criteria for sowing was met when a minimum of 20 mm water in the soil profile had accumulated since the beginning of sowing window. As the dry season precedes groundnut sowing, it was also assumed that there was little or no transpirable water in the soil profile at the time the model was set to search for the sowing date. This is a valid assumption since around 80 % of annual rainfall is received over the Indian land grid points (India taken as one unit) during Kharif months from June to September (Parthasarathy et al., 1995), and the groundnut crop remains after the end of the rain, using remaining soil water. In irrigation and rainfed conditions, respectively, the model could not have sown in about 3.5 and 12 percent of the simulation's year-soil-cultivar combinations in the typical sowing window.

2.3.5. Simulation setup

Simulations were run using 30 years of gridded weather data to cover the major groundnut cropping areas. The simulations provided an estimate of growth and development parameters as well as pod yields. To assess the yield losses due to water deficit, two sets of simulations were run:

1) Potential yield (Y_p); the maximum yield of a crop cultivar grown in optimal water and nutrient supply without biotic stress (Lobell et al., 2009; van Ittersum et al., 2013).
2) Water-limited potential yield (Y_w); reflects yield under rainfed cropping conditions without any supplementary irrigation (van Ittersum et al., 2013).

Both scenarios assumed identical agronomic practices and weather input. However, in the first scenario, the model was set to irrigate the simulated crop whenever the soil dried to a specified level, therefore providing yield predictions of a fully irrigated crop. The model used the fraction of transpirable soil water (FTSW) threshold of 0.50 to trigger irrigation. The same approach was used by Vadez et al. (2017).

2.4. Model outputs and analysis

2.4.1. Drought and yield gaps

Observed and simulated geo-biophysical properties of each district described above were then analyzed in different steps:

The water deficit index (WDI), defined as the probable yield loss percentage due to water deficit for each district, were computed as follow:

$$\mathrm{WDI}\ (\%) = (Y_p - Y_w) / Y_p \times 100 \quad (1)$$

The yield gap (Y_g) was estimated using the weighted potential yield (Y_{wp}), calculated according to the information on the proportion of the irrigated and rainfed area of each district.

$$Y_{wp,i} = [(Y_{w,i} \times A_{rainfed,\ i}) + (Y_{pi,\ i} \times A_{irrigated,\ i})] / (A_{rainfed,\ i} + A_{irrigated,\ i}) \quad (2)$$

Where, $Y_{wp,i}$ is the weighted potential yield, $Y_{w,i}$ is the water-limited potential yield, Y_p is potential yield, $A_{rainfed,\ i}$ is the total rainfed cultivated area of groundnut and $A_{irrigated,\ i}$ is the total irrigated cultivated area of groundnut, all in district i.

Consequently, Y_g in district i was the difference between the weighted potential yield (Y_{wp}, Eq. 2) and average farmers yield (actual yield; Y_a):

$$Y_{g,\ i} = Y_{wp,\ i} - Y_{a,\ i} \quad (3)$$

Here it should be noted that there was no year-to-year calculation of the yield gap within each district. While we had yearly production data, we had only gridded weather data, which represent the weather in any given site in a stochastic manner, not the exact weather of each year. Therefore, only an average value of yield gap could be produced for each district. This is also consistent with the literature (van Ittersum et al., 2013; Van Wart et al., 2013b; Lobell et al., 2009), where the concept of yield gap is usually expressed as average and year-to-year variation is often considered less useful. In GYGA protocol (www.yieldgap.org), a median yield is considered more representative than an arithmetic average.

2.4.2. Principal component analysis (PCA) and clustering

Agronomic outputs from the model, together with observed geo-biophysical indicators and estimates of the yield potentials and gaps gave a total of approximately 60 indicators to characterize each district. This was the raw information that served as a basis for principal component analysis (PCA) and clustering. However, a number of these indicators were tightly correlated to one another, and doing clustering among them would have run the risk of over-representing some variables. Therefore, a correlation analysis was carried out to select only those that were not correlated. After the cutoff, 17 non-correlated indicators remained, including the geography, climate variables, management and crop characteristics in both irrigated and rainfed conditions, in addition to Y_{wp} and Y_a (Table 3). These were analyzed by PCA (R software v.3.6.1). Loadings of six components (explaining >85 % of dataset variability) for each simulation unit were used to define the homogeneous production units (similarly in Chauhan and Rachaputi, 2014 and Hajjarpoor et al., 2018b).

The NbClust Package (Pašiaková et al., 2013) was used to determine the most appropriate number of clusters for the data set. According to

Table 3
List of non-correlated variables[a] used in the PCA.

Latitude (degrees)
Longitude (degrees)
Sowing date day of the year (DOY) in rainfed condition
Weighted minimum temperature (°C) of rainfed and irrigated conditions
Sum of radiation (MJ m^{-2}) during the growing season in irrigated condition
Sum of radiation (MJ m^{-2}) during the growing season in rainfed condition
Cumulative seasonal rainfall (mm) in irrigated condition
Evapotranspiration (ET, mm) during the growing season in rainfed condition
Evaporation (E, mm) during the growing season in irrigated condition
Evaporation (E, mm) during the growing season in rainfed condition
Transpiration (Tr, mm) during the growing season in irrigated condition
E/ET ratio during the growing season in irrigated condition
Weighted E/ET ratio of rainfed and irrigated conditions
Growing season period (d) in irrigated condition
Total biomass (kg ha^{-1}) in irrigated condition
Weighted potential yield (Y_{wp}, kg ha^{-1})
Actual yield (Y_a, kg ha^{-1})

[a] Not being among non-correlated variables does not indicate less importance of an indicator.

the majority rule, out of the 30 indices considered by NbClust, the optimum number of clusters was seven (distance = 'euclidean', min.nc = 3, max.nc = 9, method = 'centroid'). Each of these seven clusters, therefore, encompasses the districts with comparatively higher similarities in the loaded geo-biophysical properties (HPUs).

We have also confirmed significant differences in variables of interest between separate clusters using one-way ANOVA (showed in Suppl. Table S1). In this case, HPUs were defined as treatment and districts as replication in an unbalanced completely randomized design.

2.4.3. GxExM interactions

Actual and simulated pod yield data across years and districts, as well as water deficit and yield gap percentages in each district, were used to construct boxplots to visualize the distributions within each HPU and within the entire groundnut production area. For those with year-to-year variation, including potential yield (Y_p), water-limited potential yield (Y_w), and actual yield (Y_a), the coefficient of variation (CV) was measured to permit comparisons of variance among each HPU and with the whole groundnut production area. In other words, the CV% were used as an estimate of the degree of GxExM interactions and then to compare Y_p, Y_w, and Y_a. Later these comparisons were used as a way to pinpoint where GxExM interactions remained or where these had been reduced in comparison to the entire area. The inverse distance weighted (IDW) technique was used to interpolate variation (CV%) of actual and simulated pod yield across India. The results were visualized using ArcMap software v.10.7, and discussed further. Variations for yield gap (Y_g) and water deficit Index (WDI) among districts within each HPU were also shown via boxplot, however, as they were estimated based on averages, there was no year-to-year variation (CV%). The complete simulated dataset is presented as Suppl. Table S1, where range of variation for the different traits in each HPU and across the whole India are shown, including analysis of variance among HPU's for each trait, as a qualitative estimate of GxExM interactions and their differences among HPUs.

3. Results

3.1. Focal season and area of study, AICRP centers distribution and actual yield (Y_a)

Groundnut is cultivated in around 6 M ha in about 400 districts throughout India. While according to the official data, a decreasing

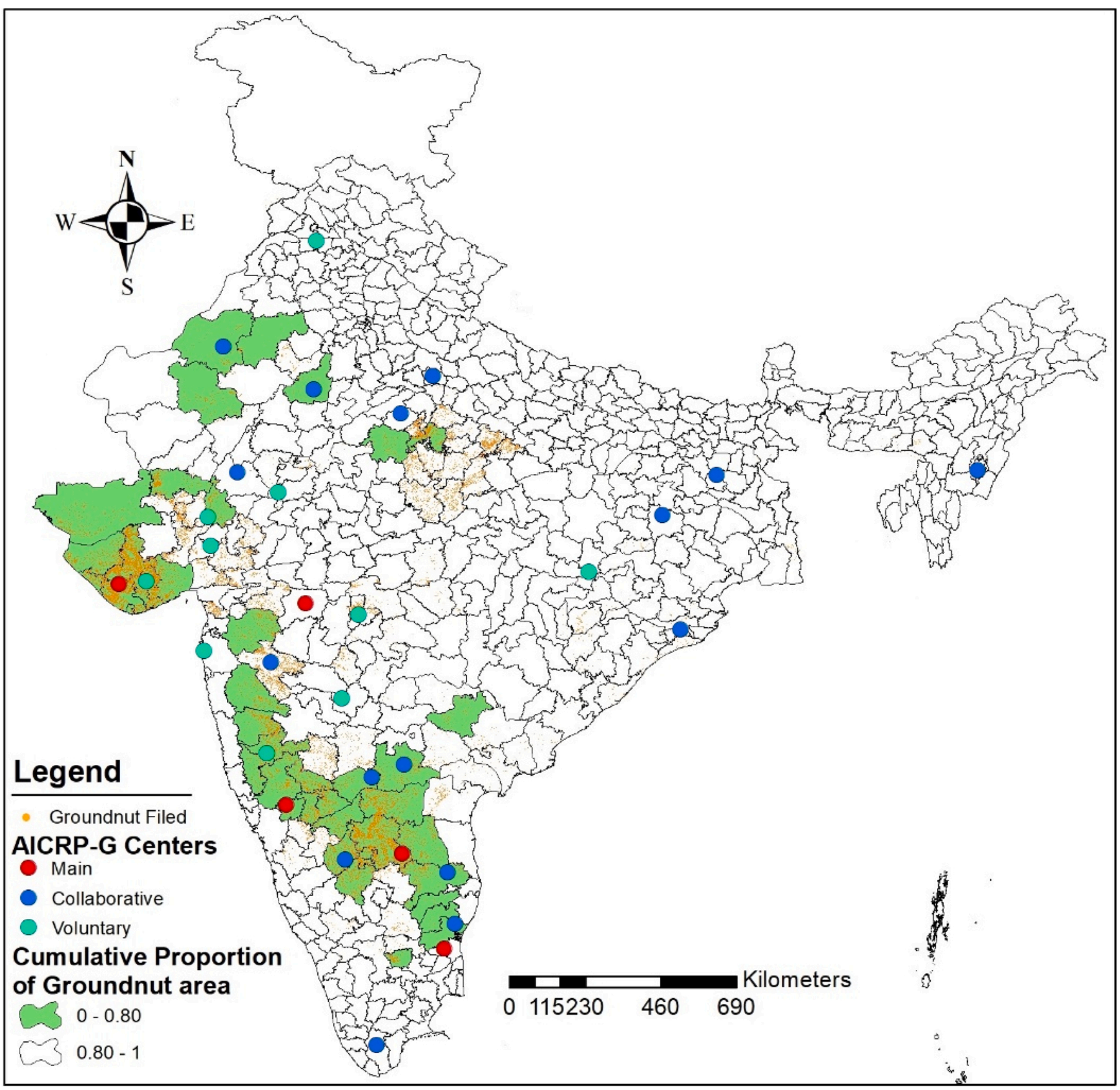

Fig. 1. Location of groundnut AICRP centers across India. Green-highlighted districts account for 80 % of groundnut production area in India according to official data and orange dots showing the location of groundnut fields according to satellite imagery data of 2013-14. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

trend in cultivated area has been seen in the recent decade, national groundnut production has stayed around 6–7 M tons due to slight yield increases. Among all districts, 40 districts accounted for 80 % of the total groundnut cropping area within the 2001–2015 timeframe. However, 19 out of 31 testing sites (5 main and 26 collaborative and voluntary, AICRP centers) were not located within the identified major groundnut production areas (Fig. 1). The current analysis was focused on the rainy season of these 40 districts plus 28 adjacent districts, whose inclusion was motivated by satellite imagery data and observed increasing trends in districts. Therefore, our analysis finally encompassed 68 districts covering ~85 % of the total groundnut cropping area (~5.1 M ha producing ~5.2 M tons, which means an actual yield of ~1 tons of pod ha^{-1}) in the base timeframe (2001–2015). Considering district levels means in the timeframe, the highest actual yields (Y_a) in the rainy season were recorded in Tamilnadu (Villupuram with 2080 kg ha^{-1}) and Rajasthan (Bikaner with 2060 kg ha^{-1} and Churu with 1950 kg ha^{-1}) and the lowest yields were associated with Karnataka (Bijapur with 435 kg ha^{-1}) and Andhra Pradesh (Anantapur with 440 kg ha^{-1}).

3.2. Model evaluation

The statistical indices for evaluation of simulated and observed values showed high accuracy for pod yield with the estimated RMSE of 53 g m^{-2} (16 % as normalized RMSE). The model also showed high sensitivity to a wide range of pod yields between 174 and 576 g m^{-2} of Y_a (Fig. 2), and particular sensitivity to water availability, that is one of the important factors affecting yield in groundnut. For further evaluation of the model, check Vadez et al. (2017).

3.3. Potential production and probable effect of water deficit

Across India, groundnut fields received variable amounts of irrigation and with a variable frequency depending on the topography and rainfall pattern of the region, access to water, financial capacity and infrastructure. The output of the model in optimal water and nutrient supply condition without any biotic stress showed an average potential yield (Y_p) of 4750 kg ha^{-1} (maximum of 5085 kg ha^{-1} in Namakkal, Tamilnadu, and minimum of 4330 kg ha^{-1} in Bharuch, Gujarat) with commonly used agronomic practices in each district. Model output under rainfed conditions gave an average water-limited potential yield (Y_w) of 2820 kg ha^{-1} (maximum of 4620 kg ha^{-1} in Haveri, Karnataka, and minimum of 300 kg ha^{-1} in Jaisalmer and Bikaner, Rajasthan, although there may be no rainfed cultivation in Rajasthan).

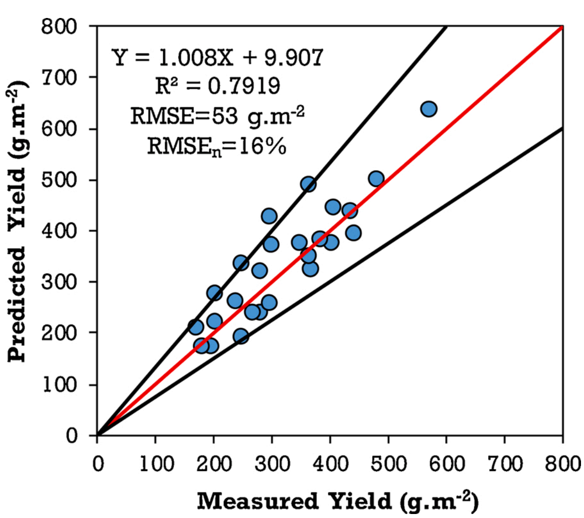

Fig. 2. Relationship between simulated and observed pod yield of 25 experimental trials in three different sites, different water regimes and different seasons across India. Black lines show 25 % upper and lower of red 1:1 line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Across India, the simulated yield loss caused by water deficit was around 2000 kg ha^{-1} on average (giving a water-deficit index WDI≈40 %, Fig. 3). The lowest risk of water deficit occurred in coastal areas like Haveri and Dharwad in Karnataka, which receive adequate rainfall and proper seasonal distribution. Furthermore, these areas are characteristic with deep soils with relatively high water holding capacity. Nevertheless, WDI was more than 90 % in some districts of Rajasthan (e.g., Jaisalmer, Bikaner). Simply, North regions showed higher WDI indicating a severe potential effect of drought (Rajasthan and some part of Haryana), while WDI was medium in West and South of India (Gujarat, AP, Telangana, Karnataka, and Tamilnadu) and mild in coastal and central areas (Maharashtra and some part of Karnataka and AP) (Fig. 3). WDI is presented here as a simple indicator of the potential effect of water deficit during the season, assuming no irrigation, and without simulating its timing.

3.4. Yield gap (Y_g) and production limitations

According to the irrigation portion in each district, weighted potential yield (Y_{wp}) was estimated to be 3610 kg ha^{-1} on average across all districts with a range among districts of 2080 - 4990 kg ha^{-1}. The yield gap (Y_g) was calculated as the difference between Y_{wp} and Y_a in each district. The Y_g across all districts averaged ~2535 kg ha^{-1} and varied between 890 and 3875 kg ha^{-1} (i.e. 36–88% of Y_{wp} with a mean Y_g of ~70 %). It should mention that, while potential yields and Y_a were respectively simulated and observed from 30 years and 15 years of data, Y_g values were just one per district.

The spatial distribution of Y_{wp} and Y_g is shown in Fig. 4. This map shows that only a few districts had a small Y_g, indicative that recommended management practices were used by farmers in these districts, like in Gujarat, a state famed for groundnut production. The lowest Y_g was observed in its districts Banas Kantha and Kachchh with 890 and 925 kg ha^{-1}, respectively (equal to 36 and 39 % of Y_{wp}, respectively). However, the lowest Y_{wp} was obtained in the same state in Rajkot with 2085 kg ha^{-1}. Some of Tamilnadu's districts in the South also showed low Y_g, such as Salem and Namakkal, with 945 and 960 kg ha^{-1}, respectively (equal to 36 and 37 % of Y_{wp}, respectively).

Comparing Figs. 3 and 4 highlights districts in northern regions with a high Y_g, where severe water deficit is possible, whereas the highest Y_{wp} was also obtained in this area in Sikar and Jodhpur, with respectively 4990 and 4965 kg ha^{-1}, as around 90 % of groundnut production in this area is under irrigation. Even with irrigation, part of the specific difference between actual and attainable yield (Fig. 4) can be explained by the effect of water deficit (compare with Fig. 3), possibly due to the mismanagement of available water. On the contrary, some coastal and central regions also showed high Y_g (Fig. 4), although these gaps were not drought-related (Fig. 3), suggesting a role for constraints like biotic stress and/or poor agronomy. Accordingly, the highest Y_g was visible in Haveri and Bagalkot in Karnataka, respectively, with 3875 and 3750 kg ha^{-1} (equal to 83 and 84 % as a percentage of Y_{wp}) and the highest Y_g in percentage occurred in Mahoba, UP and Bijapur, Karnataka (both 88 %, equal to 3315 and 3135 kg ha^{-1}, respectively).

3.5. Homogeneous production units (HPUs) and their characteristics

The loadings of main PCs specific for each district were clustered into seven bio-geophysical units, termed homogeneous groundnut production units (HPUs, Fig. 5). The number of clusters was optimized according to the majority rule of 30 indices, provided in NbClust Package (Pašiaková et al., 2013), along with qualitative interaction with breeders. The details of each HPU are summarized in Suppl. Table S1, visualized in Fig. 5 and the projected production of these units is captured in Fig. 6. PCA biplot and dendogram graphs were added as Supplementary material (Suppl. Fig. S2 and S3).

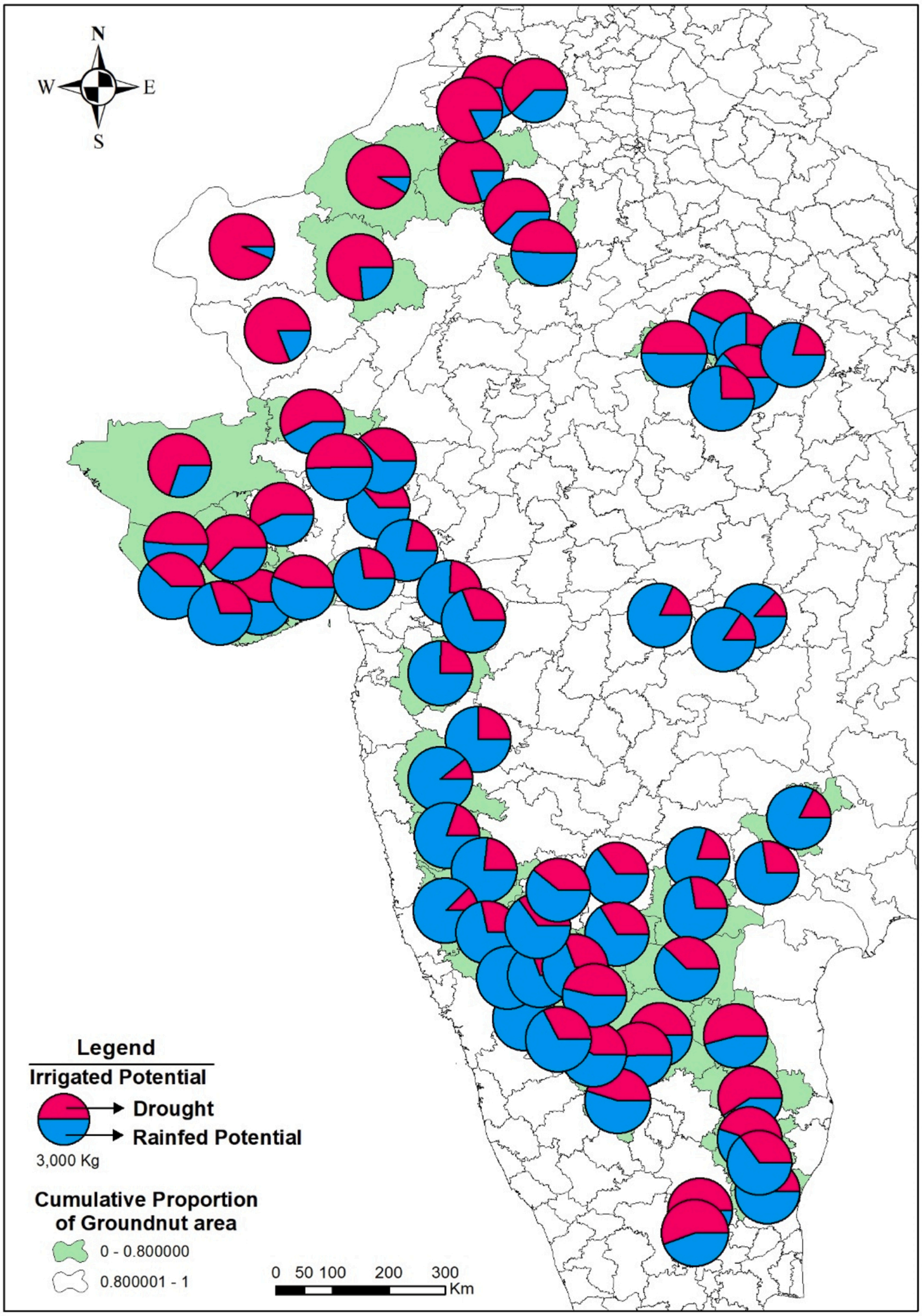

Fig. 3. Distribution of water deficit effects on groundnut production in India. The diameter of the red and blue pie charts indicates the simulated yield potential (Y_p). The blue proportion reflects the water-limited yield potential (Y_w) and the red segment reflects potential yield loss due to water deficit. Green-highlighted districts encompass 80 % of the groundnut production area in India. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

HPU1 - visualized in red, included eight districts of Rajasthan as well as two districts of Haryana, northern India (~5 % of investigated area and ~8 % of production share - ~90 % irrigated - ~63 % Y_g). The rainfed groundnut cultivation of this HPU could be mostly affected by drought (73 % potential yield reduction). The yield potential was the highest of all HPUs, as a result of the long growing season and high cumulative radiation. Also, a low ratio of evaporation by evapotranspiration (E/ET ratio) was observed, suggestive of higher water use efficiency in this HPU. Weather data indicated a frequent occurrence of high temperatures during the growing season (higher than 40 °C).

HPU2 - visualized in green, included 13 districts of Gujarat, western India and three districts in the central part of India (~38 % of investigated area and ~46 % of production share - ~11 % irrigated - ~56 % Y_g). The low yield gap in this HPU indicated appropriate management practices although the yield potential appeared to be limited by low-radiation (Suppl. Table S1). Optimum temperatures during the growing season lead to a short growing season.

HPU3 - visualized in light green, included 16 districts in a large area of central India from Maharastra, AP, UP, Karnataka, MP and Gujarat (~7% of investigated area and ~8% of production share - ~38 % irrigated - ~80 % Y_g) also experienced radiation-limitation production like HPU2 but had a relatively high yield gap, which indicated mismanagement and the likely effect of biotic stresses in general (possible associated with high rainfall).

HPU4 - visualized in blue, included two coastal districts of Maharashtra and two of Karnataka (~3% of investigated area and ~4% of production share - ~12 % irrigated - ~78 % Y_g). It was characterized by the highest rainfall and a high yield gap. Production could be

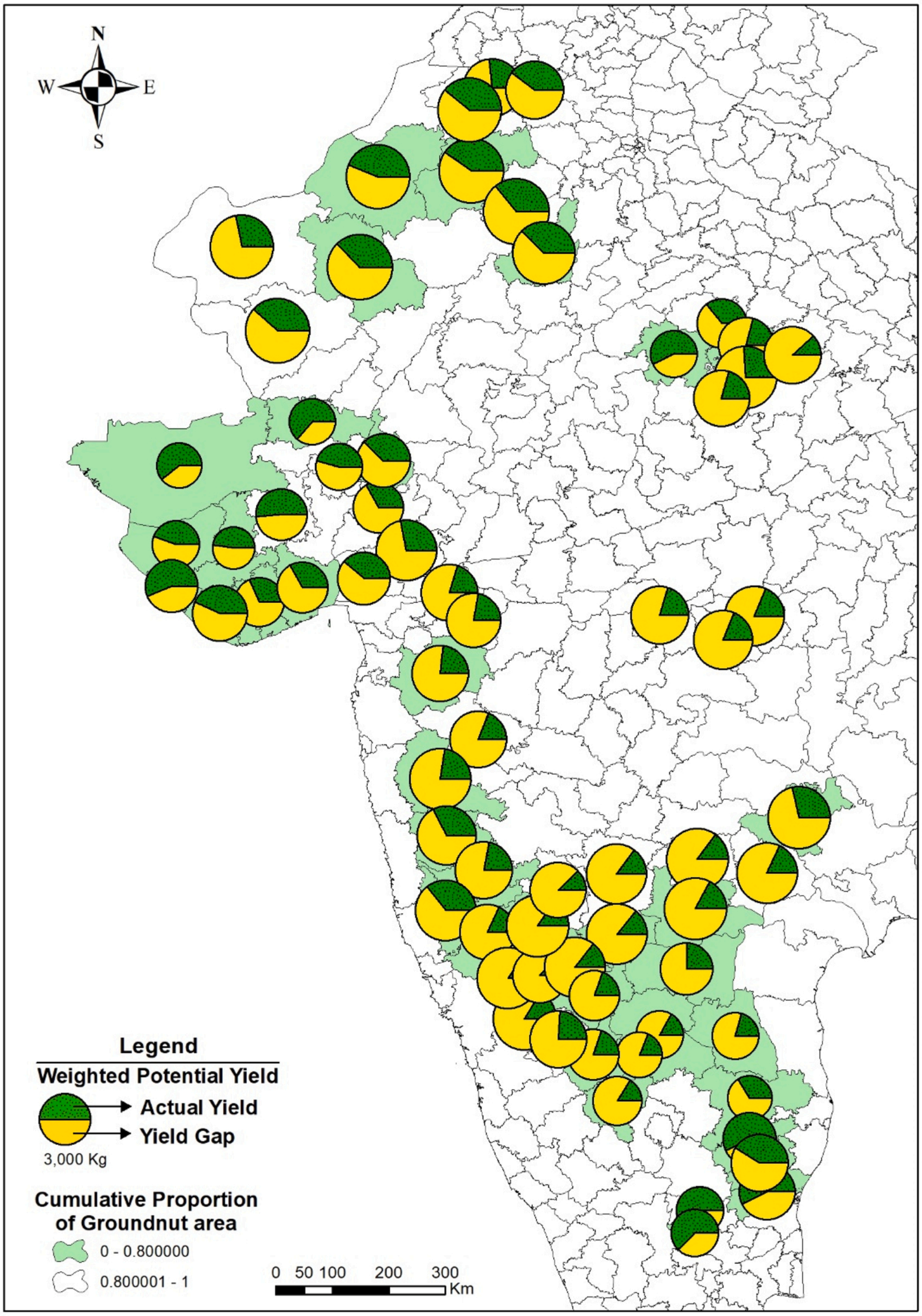

Fig. 4. Yield gap distribution across the main groundnut production tract in India. Pie chart diameter indicates weighted potential yield according to the irrigation proportion (Y_{wp}), which takes into account common irrigation practices at the district level. The green segment of each pie chart indicates actual yield (Y_a) and the yellow portion indicates the yield gap (Y_g). Green-highlighted districts encompass 80 % of the groundnut production area in India. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

constrained by biotic stresses, poor input usage and agronomy.

HPU5 - visualized in yellow, included six coastal districts of Maharashtra and three of Karnataka (~10 % of investigated area and 7 % of production share - ~24 % irrigated - ~81 % Y_g). It had the highest yield gap. The occurrence of low temperatures likely contributed to delayed phenological development in this HPU.

HPU6 - visualized in light orange, included four districts of Andhra Pradesh, South of India and one of Karnataka (~30 % of investigated area and 18 % of production share - ~9% irrigated - ~78 % Y_g) is ranked second by cultivated area after HPU2. It was characterized by the lowest actual yield and the lowest potential comparing to other HPUs. Drought was an issue in this HPU. Radiation constrained yield in this HPU but potential yield also could be, at least partially, limited by the cultivar production potential.

HPU7 - visualized in orange, included five districts of Tamilnadu, southern India and two of Karnataka (~7% of investigated area and 10 % of production share - ~33 % irrigated - ~55 % Y_g). Its characteristics were the lowest yield gap among other HPUs and high water use efficiency (lowest E/ET ratio), suggesting adequate management practices.

3.6. Exploitable production gap

While proper estimations are needed to determine economic yield based on input and output prices (Fischer, 2015; van Dijk et al., 2017), approaching 70–85 % of potential yield is typically considered possible under good farm management (Fischer et al., 2014; Lobell et al., 2009; Timsina et al., 2018; van Ittersum et al., 2013). In major groundnut production regions of India, closing yield gaps to 80 % of Y_{wp} would

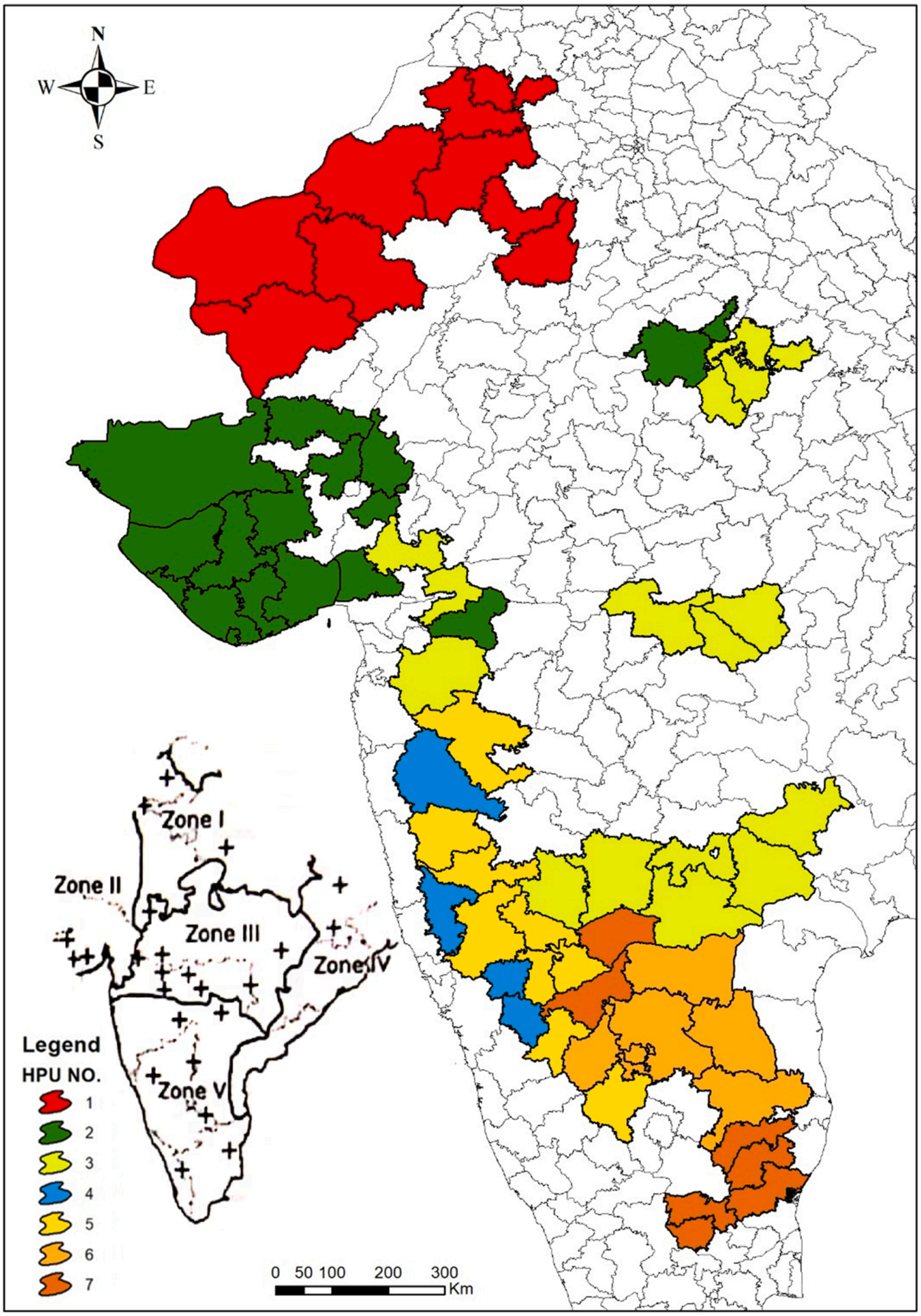

Fig. 5. Results of the cluster analysis grouping primary groundnut producing districts into seven Homogenous Production Units (HPUs) (denoted by color), according to similarities in geo-biophysical characteristics, observed yield productions, and model output. Highlighted districts encompass more than 85 % of the groundnut production area in India. Inset shows the traditional groundnut zonation visualization, cited in Witcombe et al. (1998). Colors have no meaning other than to distinguish HPUs.

mean a production increase of ~8 M tons across seven major HPUs, which is called exploitable production gap (Fig. 6). The production ratio in Fig. 6 is a ratio of projected and current production in each HPU, which take into account both the magnitude of the yield gap, and the area under cultivation in the same HPU. In that way, result showed a low production ratio in HPU2, but a high exploitable production gap, indicative of low Y_g but a large area under groundnut cultivation. On the contrary, a high production ratio and a high exploitable production gap in HPU6 indicated a high Y_g combined to a large area.

3.7. GxExM interactions

Interpolating the coefficient of simulated yield variations across years within India showed that Y_p was very homogenous (Fig. 7a) whereas temporal variation in Y_w was high (Fig. 7b) in some areas with medium to low average seasonal rainfall. The stark contrast between Y_p and Y_w was explained by irrigation practices, which is plotted as an interpolated Y_{wp} coefficient of variation map (Fig. 7c). The latter revealed that production potential could fluctuate year to year especially in areas with less irrigation water availability and a medium amount of rainfall during the season, such as Gujarat in the West (HPU2) and Andhra Pradesh in the South (HPU6) where the distribution of rainfall is also a determinant. Large year-to-year variations were visible for Y_a (Fig. 7d), except in the North where groundnut was mostly irrigated or coastal areas of Karnataka with high rainfall, and then where the variation in Y_a data looked like the variation in the Y_p data.

Spatio-temporal variations in pod yield across years and districts within each HPUs, and the entire groundnut production area was

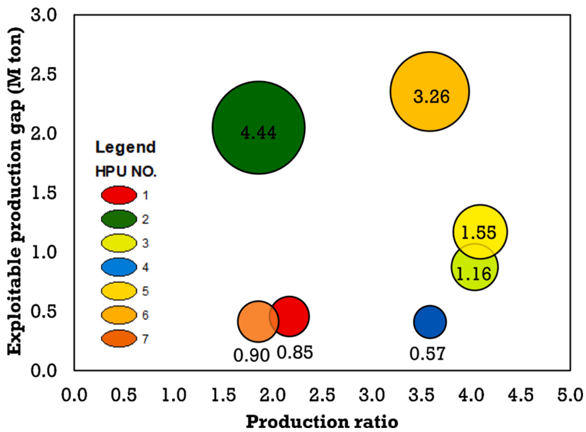

Fig. 6. Relationship between the exploitable production gap and the production ratio for each of the seven Homogeneous Production Units (HPU). Circle diameter indicates relative projected production, and printed numbers are projected groundnut production, in M tons. The exploitable production gap is the difference between current production and projected production if the yield gap was bridged to reach 80 % of potential yield. The production ratio is the ratio of projected and current production in each HPU. Refer to the discussion section for more explanation.

visualized using boxplots (Fig. 8). Under irrigation, the simulated yield for India during years and districts varied from 2655 to 5780 kg ha^{-1}, and as expected, the variation was low (CV = 7.5 %). On the contrary, under rainfed conditions, the simulated yield during years and districts for India varied from 10 to 5550 kg ha^{-1} with high variance (CV = 40 %). Despite the fact that a smaller number of districts were used to calculate these CVs in each HPU, the variation in water-limited potential yield within HPU was less than or close to values for the whole of India (13 %<CV < 45 %). The exception was HPU 1 with high variation in water-limited potential yield (CV = 83 %), which is consistent with the strong negative effect of drought in this HPU (Fig. 8). By contrast, actual yield ranged between 70 and 3180 kg ha^{-1} during years and districts with a larger CV range of 30–56% within HPUs. The CV of actual yield for India was 56 % and while without mentioning the outliers (Fig. 8, boxplots), variation within HPU was reduced considerably with the exception of HPU 7 (CV = 51 %). As the estimations of the yield gap and WDI were based on averages, there was no year-to-year variation (CV%) for them; however, variation for the yield gap and WDI among districts within each HPU are shown in Fig. 8.

4. Discussion

Large yield gaps in groundnut production across India were shown, with large variations by district. Drought had a major yield-reducing effect, which varied extensively among districts. These results highlighted the need to subdivide large production environments into smaller subdomains. Clustering of agronomic modeling output together with geo-biophysical variables led to the identification of seven HPUs, which generally showed reduced GxExM interactions and well-defined production-limiting constraints. Following proper agronomy practices, India could almost triple groundnut production by reaching attainable yield (80 % of Y_{wp}) and filling the exploitable production gap. These results emphasized the importance of identifying the nature of the target population of environments (TPEs) in improving breeding programs. A summary of findings is provided in Table 4 and Suppl. Table S2.

4.1. Definition of HPUs and its implications

Yield suffered large spatial variability under water deficit (Figs. 3 and 4). In addition, temporal variation in yield was high (Fig. 7) and depended on rainfall pattern and amount. These high spatio-temporal variations highlighted the need for subdividing large production environments, spanning large temperature or precipitation gradients, into smaller subdomains (Sciarresi et al., 2019) that offer a better resolution of factors affecting yield. Varying patterns of water deficit led indeed to varying degrees of yield reductions, as also found in different crops and regions (Battisti and Sentelhas, 2019; Chenu et al., 2011; Heinemann et al., 2015; Kholová et al., 2013). The stress patterns, as classified by the model outputs, also differed in frequency across the HPUs, suggesting that there may be a need for different breeding/agronomic packages in each target population of environment (Sinclair et al., 2020) (Table 4). This improved our understanding of the nature of the TPEs, and this is a critical component of improving the efficiency of a multi-environment testing program (Cooper and Byth, 1996). Besides, it allows optimization of multi-environment testing sites distribution, to avoids redundancies or over-representation (See section 4.4). In short, the analysis that was done in this work helps to avoid testing the genotypes in less relevant sites and selection of genotypes in abnormal years which do not sufficiently represent the most frequent environmental scenarios occurring at the particular TPE (Kholová et al., 2020). While finding the required number of HPUs can be made to vary according to the user and the index used, a wide variety of indices have been proposed to find the optimal number of clusters (Pašiaková et al., 2013). However, selection of the seven HPUs (Fig. 5) was found optimal, although it was not the only possible number. The choice of seven HPUs in this study was both the result of unbiased quantitative analysis, and interaction and consensus with the breeding community of Groundnut Network Group-Asia (GNG-A).

Overall there were major changes in our proposed zonation, confirming our initial hypothesis. According to the defined HPUs, the border between the classical zone I and II shifted to lower latitude, so that no more districts of Rajasthan is in zone II. It can be due to increasing water deficit in the North as HPU1 is characterized by it. Classical zone III expanded in the center of India and formed HPU3 with a high yield gap and likely effect of biotic stresses. While there was not enough groundnut production area in classical Zone IV to reach the threshold for this kind of analysis but several HPUs (HPUs 4, 5, 6, 7, and one part of HPU3) were observed in classical zone V with different constraints, e.g. drought effects, rainfall amount, radiation and definitely different yield gaps because of different agronomy practices and lack of a proper genotype in some part of this zone (see Suppl. Fig. S4). As more than half of the groundnut area in India was located in this heterogeneous area, it could also be a good objective for targeted breeding programs.

4.2. The particular case of drought/heat in HPU1, 2 and 6

Drought stress is often associated with high temperatures in semi-arid production environments that together may have compounding adverse effects on groundnut productivity (Janila et al., 2016). Though groundnut vegetative growth is well adapted to high temperatures (Vara Prasad et al., 2000a, 2000b), reproductive processes are sensitive (Craufurd et al., 2003; Hamidou et al., 2013; Vara Prasad et al., 2000a, 2000b). In that sense, HPU1 was different from HPU2, 6 and 7, in that in HPU1 the potential effect of water deficit was significantly higher than other HPUs and the average maximum temperature was ~37 °C (during groundnut growing seasons in simulation years). We suspected both drought and heat stress could occur in HPU1. Therefore, daily w ather data were investigated. Although earlier findings showed that heat stress is not a major determinant for groundnut yields in the current climate of India (Challinor et al., 2007), we found frequent occurrence of high temperature with many days having a high temperature between 40–50 °C. Ntare et al. (2001) showed that the pod yield of groundnut genotypes declined by more than 50 % when flowering and pod formation occurred at maximum temperatures averaged 40 °C. Vara Prasad et al. (2000a, 2000b) also found a reduction of 6.9 % in fruit-set of groundnut per each degree higher than 36 °C. These are similar results that were found in

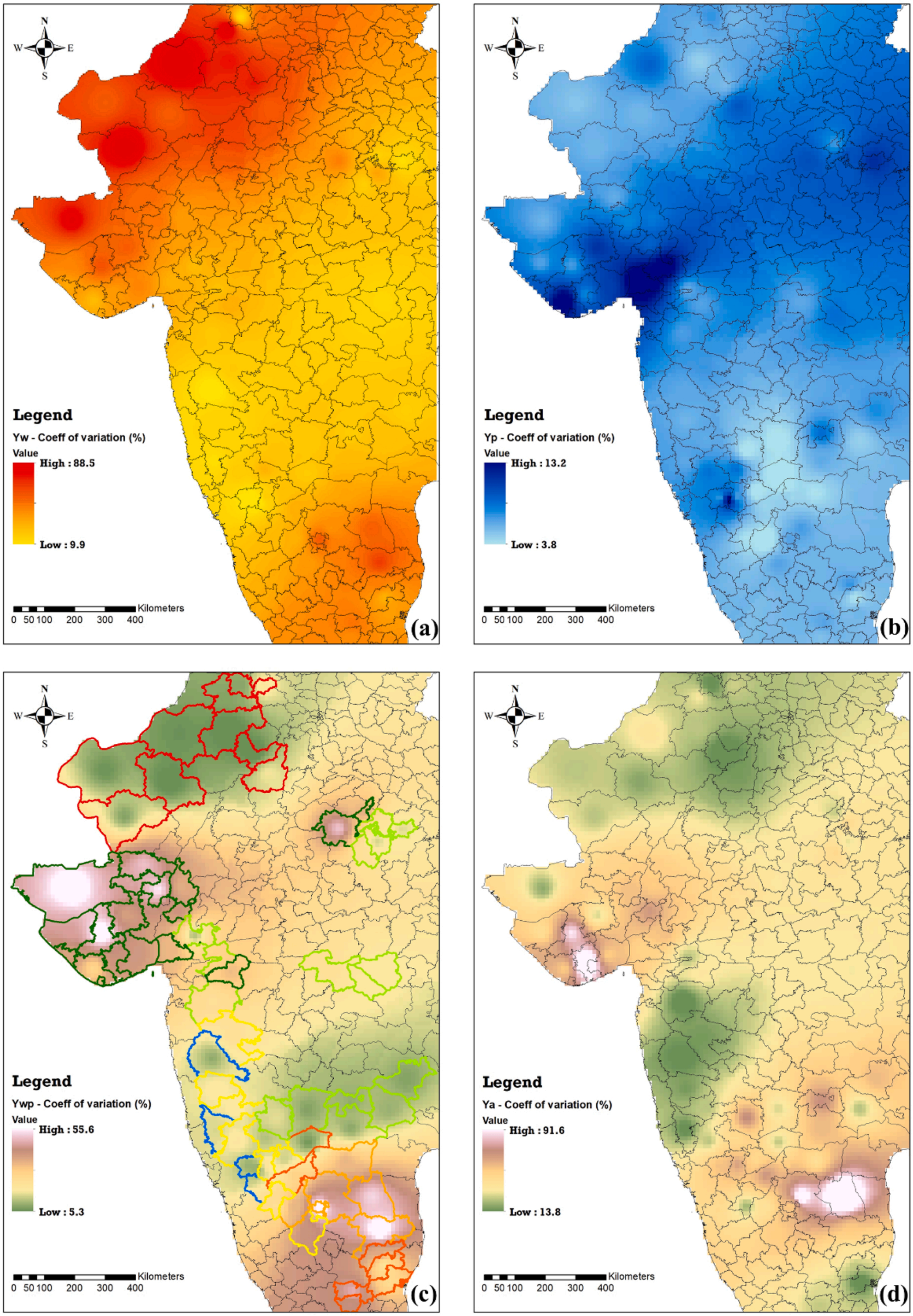

Fig. 7. Interpolated coefficient of variation of potential yield (Y_p, a), water-limited potential yield (Y_w, b), weighted potential yield (Y_{wp}, c), and actual yield (Y_a, d). HPU borders are shown only in panel c.

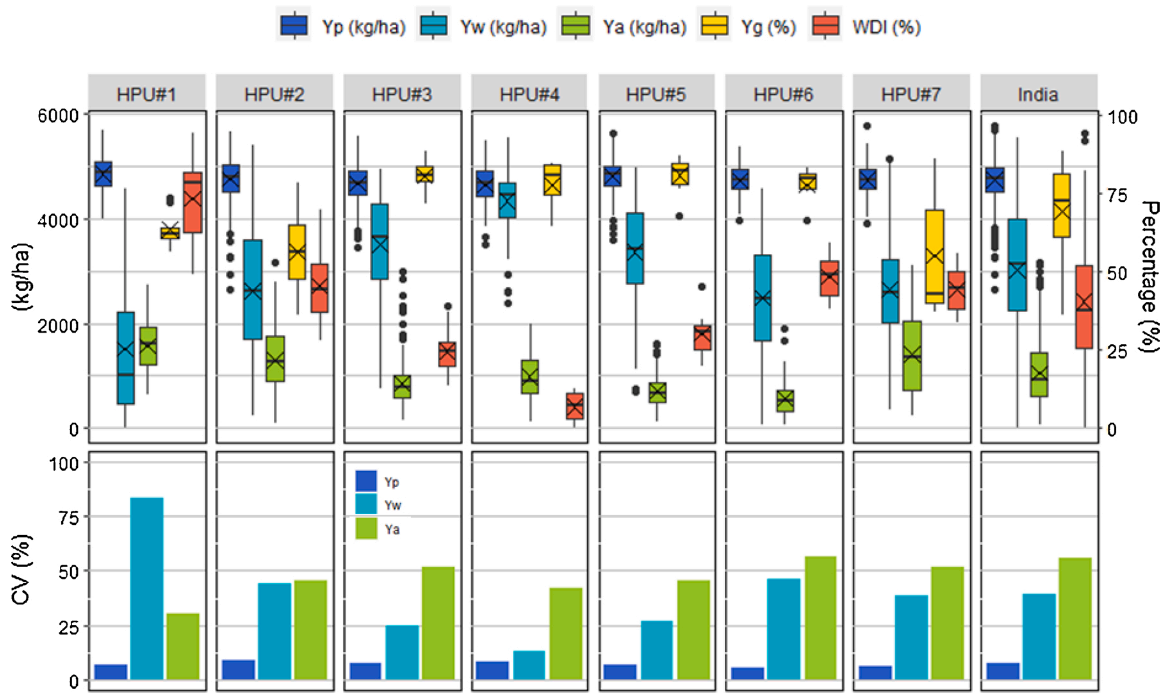

Fig. 8. Boxplots showing the variation in potential yield (Y_p), water-limited potential yield (Y_w) and actual yield (Y_a) in kg ha^{-1} across years and districts within each HPU's and within the entire groundnut production area, in addition to the yield gap (Y_g) and water deficit Index (WDI) in percentage across districts. Edges of box show 25 and 75 percentiles, horizontal line inside the box shows the median and the continuous lines show minimum and maximum. Averages are marked with crosses and outliers with circles. The coefficient of variation (CV) percentage is also shown in bar charts as an indicator to compare the range of variation in simulated and actual yields.

Table 4
Summary of HPU characteristics, agronomy recommendations, breeding solutions, and groundnut production potential gaps. An extended version of this table is provided as Suppl. Table S2.

Homogenous Production Unit	**Agronomy recommendation(s)**	**Breeding solution(s)**	**Projected production potential (Low (< 1 M t) Medium (1<X<3 M t) High (> 3 M t)) - Relative share of production – Yield gap**
HPU1 (in red), 8 districts of Rajasthan - two districts of Haryana, northern India (5% of area)	-Irrigation-management - Water-conservation	- Temperature tolerance - Short duration (escape) - water use efficiency	Low (0.85 M t). Small production share - Medium yield gap
HPU2 (in green), 13 districts of Gujarat, - three districts in central India (38% of area).	- Maximizing light capture - Water-conservation	- Drought-adapted cultivars - Longer duration - Higher radiation use efficiency (RUE)	High (4.4 M t). Large production share - Low yield gap. High production potential, exploitable by breeding for high yield. Important hotspot target for breeders.
HPU3 (in light green), 16 districts in central India (Maharastra, AP, UP, Karnataka, MP and Gujarat) (7% of area)	- Agronomic practices - Integrated biotic stress management - Maximizing light capture	- Pest /disease resistance - Longer duration cultivar - Higher radiation use efficiency (RUE)	Medium (1.16 M t). Medium production share. High yield gap.
HPU4 (in blue), 2 coastal districts of Maharashtra and two of Karnataka(3% of area)	- Integrated biotic stress management	- Pest and disease resistance	Low (0.57 M t). Low production share. High yield gap.
HPU5 (in yellow), 6 coastal districts of Maharashtra and 3 of Karnataka(10% of area)	- Sound agronomic practices	- Shorter duration cultivars	Medium (1.55 M t). Medium production share. A Medium to high yield gap.
HPU6 (in light orange), 4 districts of Andhra Pradesh, South of India and one of Karnataka (30% of area)	- Sound agronomic practices - Water-conservation - Maximizing light capture	- Drought-adapted cultivars - Longer duration - Higher radiation use efficiency - Higher yield-potential	High (3.26 M t). High production share. High yield gap. Hotspot target for breeders and agronomists.
HPU7 (in orange), 5 districts of Tamilnadu, southern India and 2 of Karnataka (7% of area)	- Water-conservation - Maximizing light capture	- Drought-adapted cultivars - Longer duration cultivar - High radiation use efficiency	Low (0.90 M t). Small production share. Lowest yield gap.

Niger (Hamidou et al., 2013), where yield in irrigated summer trials was reduced, whereas vegetative biomass was not. Hence, high-temperature tolerance would be an important breeding target in the mostly irrigated cultivation area of HPU1. Breeding for short duration groundnut as an escape mechanism to avoid end-of-season moisture stress and development of water use efficient cultivars, which is currently happening in HPU1 (Janila et al., 2016), would be suitable only for the relatively small rainfed part of HPU1. In other HPU's facing drought issues, i.e. HPU2, 6 and 7, temperatures were checked and are currently not high enough to directly cause heat stress (as already reported by Challinor et al., 2007). Therefore, the breeding target in these HPUs (2, 6 and 7) would be drought adaptation (Table 4). Identifying HPUs with high prevalence of drought is also useful to better target and anticipate aflatoxin contamination issues. Aflatoxins are a major constraint affecting groundnut quality globally and their incidence is favored by drought and high soil temperature. More care should be given in these environments, especially concerning post-harvest management, reported as the leading way to avoid aflatoxin contamination (Kumar et al., 2017; Waliyar et al., 2015).

4.3. Growing cycle duration and radiation limitation in HPU 2 and 6

Cumulative radiation limited yield in HPUs 2 and 6, and to a certain extent in HPU 3 and 7, likely from a combination of greater cloud cover and sub-optimal growth cycle duration. Temperatures in these HPUs were within the optimal range (28−30 °C) for groundnut development (Suppl. Table S1; Table 4). Then, in these HPUs (2, 3, 6, and 7), a longer duration cultivar would have higher potential yield (especially true in HPU3 with higher seasonal rainfall), provided water did not become limiting and the field was not used by another crop after groundnut harvest. Sub-optimal temperatures delayed phenological development in HPU4 and HPU5. Shorter duration cultivars would then be beneficial in some parts of HPU5, where water deficit is an issue. Maximizing radiation capture while matching growth to water availability will optimize yield in all HPUs.

4.4. GxExM interaction aspects

The benefit of grouping the groundnut production region in India into HPUs is evident with the boxplots and CV% variation in Fig. 8. In most cases, variations of actual and simulated yields across years and districts within HPUs were less than values reflecting all groundnut production areas. These results showed that the degree of GxExM interactions then decreased within HPU, and therefore that there is an opportunity for breeding program to undertake these TPE analyses to reduce the degree of GxExM interaction that traditionally hampers progress in the rate of genetic gain. However, in some HPUs and variables, the GxExM variance was as large as the variance for the entire groundnut production area, for example the variation of Y_w remained high in HPU1 (CV = 83 %). However, groundnut cultivation was mostly under irrigation conditions in this HPU (90 %), so that variations of Y_a were limited (CV = 30 %) and the consequence on Y_g was low (Fig. 8). Here is a situation where GxExM interactions have been mostly solved by an 'M' intervention in the form of irrigation.

Another example was HPU7, where even though high heterogeneity in Y_g was observed, similarities in other variables, and modeling outputs categorize those districts within the same HPU. In this case, two districts of Karnataka with low Y_a were grouped with five districts of Tamilnadu with high Y_a due to similar yield potentials and production limitations like drought constraints (Fig. 8). These results also suggest that it is not reasonable to expect uniform minimization of all variables in each HPU. Hamidou et al. (2013) studied a wide genotypic variation for pod yield, haulm yield and harvest index of groundnut. They found significant genotypic and interaction of genotype-by-environment, including water and temperature regimes. The magnitude of GxE, therefore, suggests that the selection for superior genotypes is specific to the screening environment. They concluded that according to the target environment, the water treatment and the yield and stability, different genotypes could be recommended.

Plant breeders and agronomists have developed different methods to deal with GxExM interactions within their respective domains (Cooper et al., 2020). Nonetheless, the potential importance of GxExM interactions for improving on-farm crop productivity has been recognized in various studies (e.g. Cooper et al., 2020; Fischer et al., 2014; Ramirez-Villegas et al., 2020). The outcomes of this study can accelerate groundnut improvements and guide targeted breeding programs. In this regard, number and location of testing sites should be optimized according to homogeneity and heterogeneity of a given area. Year to year variation at a particular site (Fig. 7) should be balanced with spatio-temporal variation among sites (Fig. 8) to find the optimum number and locations of sites in an HPU. Larger exploitable production gaps (Fig. 6) justify more testing sites.

4.5. Bridging the exploitable production gap

Across most crop-region combinations in the last two to three decades, actual yield progress has been associated with both yield gap closing via optimal management (George, 2014) and genetic gains for yield (Fischer, 2015). Even though the potential of new cultivars has not been addressed in this study, a large yield gap (Fig. 6) was found, which could be filled by proper agronomy practices (Fischer et al., 2014) and by efficiently exploiting the yield potential of existing germplasm (George, 2014). Undoubtedly, genetic improvement (Hall and Richards, 2013) can help lift the actual yield simultaneously.

Reasons for the Y_g variations are different across HPU's, although there are two significant groups based on the magnitude of Y_g (Suppl. Table S1); HPUs 3, 4, 5, 6 with 77.5–80.5 % Y_g versus HPUs 1, 2, 7 with 55–63 % Y_g. Biotic stresses were a likely constrain for production in HPU4 and likely HPU3 because of conditions favoring disease (high rainfall and humidity, Suppl. Table S1; Table 4), indicating the need for proper integrated biotic stress management (Ghewande and Nandagopal, 1997; Pandya and Saraf, 2013). Here, breeding could also participate in bridging the gap by introducing greater resistance to pests and diseases (Janila et al., 2016), while the growers are now adopting improved disease and pest management practices. Independently of disease, poor agronomy may have constrained production in HPUs 5 and 6. On the contrary, better agronomy practices in the remaining HPUs resulted in lower Y_g. Unavoidably, part of the yield gap remained unexplained, which could be due to different reasons like the issue of salinity in part of groundnut production areas, which had not taken into account by the model.

Nevertheless, even within a unit with a low yield gap like HPU2, it is worth working on bridging the gap where cultivation areas are large (Fig. 6, Suppl. Table S1; Table 4). The exploitable production gap in Fig. 6 represents the difference between current production and projected production if the yield gap was bridged to attainable yield (i.e. 80 % of Y_{wp}). The "exploitable production gap" is a more useful term than "yield gap" because attainable yield, as well as the area under cultivation, are embedded in it. Hence, even if the lowest production ratio occurred in HPU2, narrowing the yield gap in Gujarat (HPU2, green circle) could have a big effect on the groundnut production of India because of the high exploitable production gap (Table 4). Accordingly, when a high exploitable production gap coincides in a region with a high production ratio like Andhra Pradesh (HPU6, orange circle), then bridging the gap would be strategic.

4.6. Potential drawbacks and future directions

The presented work engaged the groundnut experts since the beginning and the results appeared well-aligned with the reality on-the-ground, although potential drawbacks remain. Despite the advances in crop modeling, the development and use of pest and disease sub-models are not holistic and powerful enough (Donatelli et al., 2017; Ramirez-Villegas et al., 2020). As such, the SSM model could not simulate pest and disease outbreaks. We took into account the impact of pests and disease in a qualitative manner as possible yield-reducing factors (i.e., causing Y_g). A remedy to current approaches and methods could be overlaying quantitative biotic stress data on top of the HPUs map which would help interpreting the causes for the yield gap. Our data set and HPU clustering approaches are amenable to inclusion of biotic stress data. Modelers face the perennial challenge of incomplete reference data. Increasing data availability would improve the robustness and applicability of simulation models (Donatelli et al., 2017).

5. Conclusions

The framework presented here extends from previous works (Hajjarpoor et al., 2018b; Kholová et al., 2013) focused on characterizing the main production limitations and could be applied to other major crops to help accelerate breeding gains. This study demonstrated that *in-silico* geospatial assessment could be used to guide breeding programs and accelerate crop improvement efficiently. Key production-limiting constraints were identified for each homogenous production unit (HPU). Weaker GxExM interaction within HPUs was a major contribution of this study, which would help breeding programs to choose better testing sites that better represent production variation. We posit that the clustering of groundnut production area into seven HPUs is more appropriate and useful than the classical groundnut zonation. This classification can be used to target novel crop improvement strategies beyond traditional serial research approaches. The production ratio and exploitable production gap terms (Fig. 6) can be used as a way to prioritize breeding and agronomic intervention decisions and objectives. HPU 2 (Gujarat) and 6 (Andrea Pradesh) were identified as strategically important hotspots for targeted breeding because of the high area under cultivation and high production ratio. Besides, large exploitable yield gaps could be narrowed by adopting sound agronomic practices to produce 8 M ton more groundnuts in India with the same genotypes and area under cultivation.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgment

The authors acknowledge the feedback provided by the groundnut researchers on the HPUs at the expert consultations held during Groundnut Network Group-Asia (GNG-A) meeting at ICRISAT during 26-27 September 2019. The data generated under a project supported by Department of Agriculture, Cooperation and Farmer Welfare of Govt. of India (DAC&FW, GOI) was used for the yield gap analysis and authors acknowledge the data shared by the project collaborators, KL Dobariya (JAU), R Vashathi (ANGRAU, SK Bera (ICAR-DGR) and N Manivannan (TNAU). The senior author was in part supported by a grant the Make Our Planet Great Again (MOPGA) ICARUS project (Improve Crops in Arid Regions and Future Climates) funded by the Agence Nationale de la Recherche (ANR, grant ANR-17-MPGA-0011). We are also grateful to MK Gumma and IA Mohammed for providing the satellite imagery data and Soumyashree Kar for helping in data analysis. The financial assistance to conduct the study in part was received from OPEC Fund of International Development (OFID). The study is conducted under CRP-Grain Legumes and Dryland Cereals (http://gldc.cgiar.org/).

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.fcr.2021.108160.

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