Environmental characterisation to guide breeding decisions in a changing climate

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Abstract

Substantial evidence now exists suggesting that agricultural yields will have to increase significantly in order to meet food needs during the 21st century. One such way of increasing yields is to develop high yielding cultivars through crop improvement. This Working Paper summarises the results of a CCAFS project named *Target Population of Environments* (TPE). The project aimed at providing actionable information to crop breeders and, therefore, inform breeding decisions. We developed and applied a methodology for classifying crop growing environments, determining stress profiles and, finally, assessing the potential benefit of improved breeding practice. We present two contrasting case studies, one for upland rice in central Brazil and another for common beans in Goiás (Brazil). Analyses are also currently being conducted for lowland irrigated rice in Colombia, and plans to conduct research on rice in sub-Saharan Africa. Results of the TPE project are publicly available in the form of dynamic maps and graphs at http://www.ccafs-tpe.org.

Keywords

Climate change adaptation; breeding; crop modelling; environmental characterisation.

Acronyms

CCAFS	CGIAR Research Program on Climate Change, Agriculture and Food Security
CIAT	Centro Internacional de Agricultura Tropical
CSM	Cropping System Model
DSSAT	Decision Support System for Agrotechnology Transfer
EG	Environment Group
Embrapa	Empresa Brasileira de Pesquisa Agropecuaria
FE	Favourable Environment
GO	Goiás
HFE	Highly Favourable Environment
LAI	Leaf Area Index
LFE	Least Favourable Environment
MAE	Mean Absolute Error
R	Pearson product-moment correlation coefficient
RMSE	Root Mean Squared Error
RRMSE	Relative RMSE
TPE	Target Population of Environments
UR	Upland Rice
WSPD	Water stress index in the CSM-CROPGRO-BEAN model

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Contents

Introduction

Agriculture faces and will continue to face multiple challenges. Most notably, the need to meet food demand for a rapidly growing and urbanising population under increasingly variable and warmer climates (Wheeler and von Braun 2013; Tilman and Clark 2014). Substantial evidence now exists suggesting that agricultural yields will have to increase significantly in order to meet food needs during the 21st century (Ray et al. 2013; van Oort et al. 2015). One such way of increasing yields is to develop high yielding cultivars through crop improvement (Chapman et al. 2012; Dingkuhn et al. 2015). Additionally, the development of novel, climate-adapted varieties that ably tolerate stresses will be key in order to respond to regional climatic changes (Asseng et al. 2014; Ramirez-Villegas et al. 2015), particularly if no mitigation policies are enforced (Müller et al. 2015).

The development of high yielding and climate-adapted crop varieties, however, requires an understanding of how crops respond to spatio-temporal variations in soil, climate and management, as well as an assessment of the main factors limiting yields. This is because genotype-by-environment interactions sometimes prevent plant breeding progress for broad adaptation and/or for adaptation to specific conditions within a region (Chenu et al. 2011). Therefore, understanding yield constraints and their spatio-temporal variations will ultimately lead to improved priority setting and more rapid progress in breeding programs.

This Working Paper summarises the results of a CCAFS project named *Target Population of Environments* (TPE). The project aimed at providing actionable information to crop breeders and, therefore, inform breeding decisions. Our method focuses on classifying growing environments and stress patterns, using a combination of controlled field trials and crop simulation models driven by observed soil, climate and management data (Sect. 2). We also present the application of the method on two crops in Brazil (Sect. 3), as well as a web-based tool for visualisation of results (Sect. 4). We conclude by setting out potential avenues for future research (Sect. 5).

Methodology

As stated earlier, our method combines field experiments, observations of environment (climate, soils) and management, and crop simulation models to develop a classification of environments and stress patterns. These classifications are then quantitatively assessed against the current breeding pipelines for the regions under study in order to assess the potential impact of stress-tailored breeding strategies. Fig. 1 presents an overview of the process. The methodology consists of seven steps, as follows:

1. The first step is to define the study region and crop under study and the crop model to be used, and to collate experimental data for model calibration and evaluation. Because breeding is a highly crop- and region-specific discipline, the area and crop under study are straightforward choices in most cases. The crop model, however, needs to be defined with care. Particular attention has to be paid to whether a well-established model has already been calibrated and evaluated for the study region [e.g. Lobell et al. (2015)], or whether the model of choice is suitable for the conditions in the study region. The selected crop model needs to be able to simulate processes that are relevant to the region. In some cases, it may be desirable to use more than one crop model in order to assess crop model uncertainty (Asseng et al. 2013). Gathering experimental data is also key to the success of this approach. Trial data should include relevant varieties in the region, should ideally be multi-location and/or multi-year, and should include both potential yield and stress-induced yield trials. Field data should be as detailed as possible, including time-varying measures of multiple plant attributes (e.g. leaf area index, organ-specific biomass), as well as weather, soils and management inputs.

2. Once the crop model has been defined and the experimental data has been collected the next step is to calibrate the crop model using a set of field experiments. To this aim, the experimental data should first be thoroughly checked for possible errors and then split into a \`calibration\` set and an \`evaluation\` set. The objective of model calibration is to adjust influential model parameters within their reasonable ranges so that modelling results are comparable to observed data (Wallach et al. 2014). Multiple methods exist to derive model parameter values for crop models (Angulo et al. 2013;

Wallach et al. 2014; Alderman et al. 2015), and some of these are already built-in and well-tested for certain crop models. However, regardless of the method, it is key to ensure that the parameter values fall within plausible ranges and represent the morpho-physiological attributes of the varieties being parameterised.

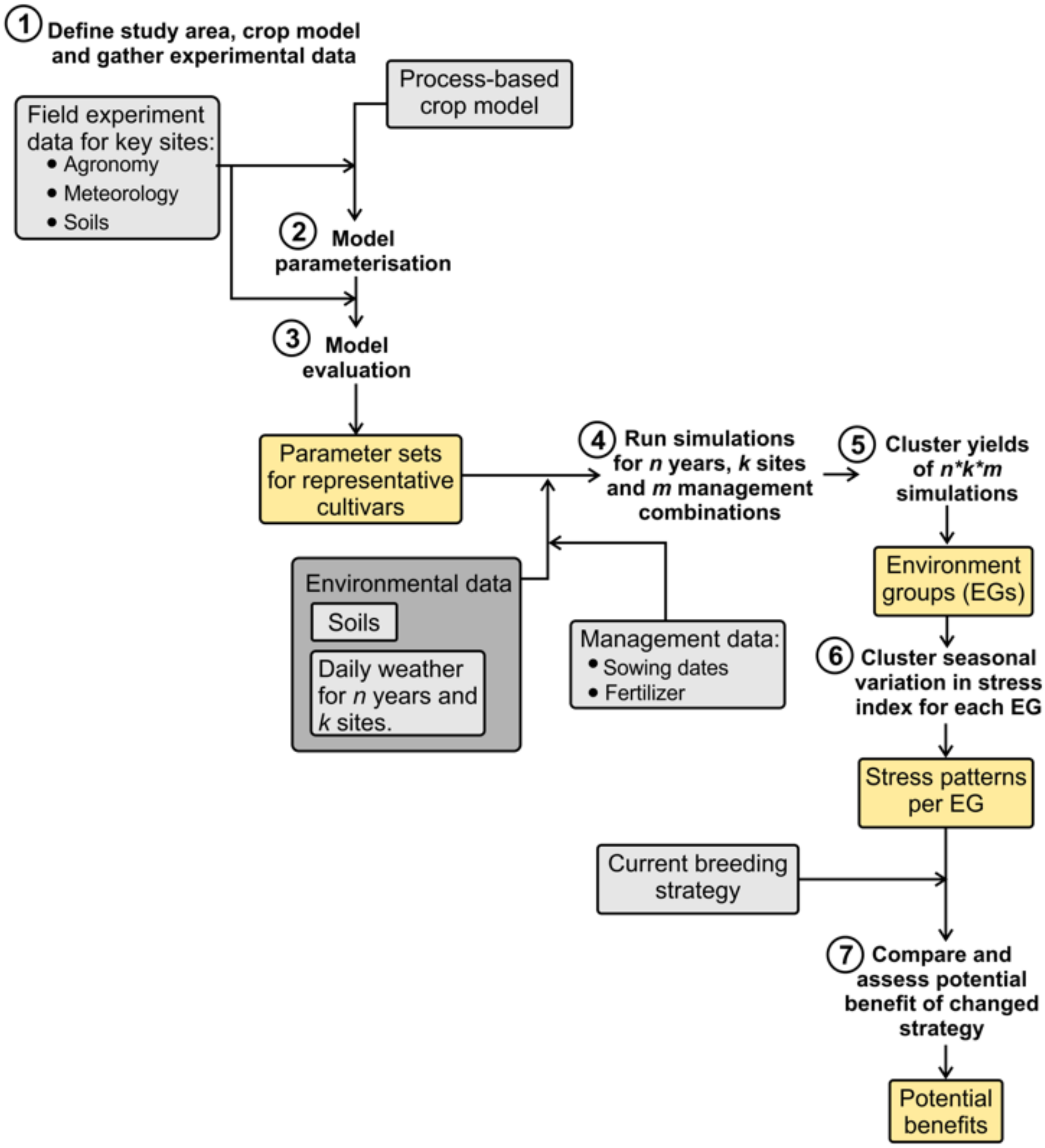

Figure 1 Overview of the environmental characterisation methodology. Circled numbers indicate steps, grey boxes indicate inputs to the method, and dark yellow boxes indicate outputs.

3. Simulations are then run per crop variety and assessed against the evaluation data. The primary aim of this step is to ensure that the model is capable of reproducing an independent set of observations. The result should be a parameter set (per variety) that can later be used to run spatially-explicit and time-varying simulations for the study region. Evaluation metrics often used in crop modelling to measure the distance between measured and simulated values include the Root Mean Square Error (*RMSE*), the *RMSE* relative to the mean or the standard deviation (*RRMSE*), the mean absolute error (*MAE*), the correlation coefficient (*R*), and the Wilmott d-statistic (Willmott et al. 2012). Model performance can also be assessed both numerically and visually through the Taylor diagram (Taylor 2001).

4. The fourth step in this process is to run spatially explicit crop model simulations for the study area (across *k* sites), for a representative period of *n* years and for a number of management scenarios (*m*). For this, either high-resolution gridded daily weather or daily weather station records of a representative number of weather stations are needed. Weather variables needed for crop simulation are: minimum and maximum temperatures, downwards shortwave solar radiation, and precipitation. Soil profile data (i.e. lower, upper and saturation moisture contents) for all locations where the crop model is to be run are also needed. Management scenarios are constructed as a combination of planting dates, planting densities, and/or fertiliser application regimes (Heinemann et al. 2015a; Lobell et al. 2015). Model runs are finally performed for each of the site*year*management situations.

5. Once simulations are completed, environmental groups (EGs) need to be determined. To this aim, statistical clustering is performed on the simulated crop yields of all the site*year*management scenarios. Clustering by yield helps separate situations of low and high yields, without necessarily assessing their causes –which will be assessed in step 6. Various clustering methods exist, including the hierarchical clustering used by Heinemann et al. (2015a) in Brazil, the k-means clustering used by Harrison et al. (2014), or more complex neural-network-based methods (Reymondin et al. 2012). Clustering efficiency and stability indicators are then used to determine the optimal number of EGs for the study region. However, it is also important to take into account the expert knowledge of regional breeders and/or agronomists to define the number of

EGs. Using the results of this first clustering, maps of EG distribution and frequency can be produced.

6. With an understanding of which site*year*management combinations belong to the different EGs, the next step is to determine the main stresses for each group, i.e. stress profiles. Because this step requires statistical clustering of stress-related modelled variables (i.e. stress index), an a-priori idea of stresses in the region should inform this step. For example, the ratio of actual to potential evapotranspiration is usually a good indicator of water stress (Heinemann et al. 2015a). Similarly, the fractional reduction in grain-set from high temperature can help differentiate heat stressed and non-heat stressed situations (Lobell et al. 2015). For nitrogen or phosphorous stress, the ratio of uptake-to-required nutrients could be used. Clustering is performed individually per EG using the seasonal variation of the relevant modelled stress index. As in Step 5, a number of clustering algorithms can be used to perform this classification.

7. The final step is to use the environmental groupings and the stress profiles to calculate how much additional area in the study region can be covered if the breeding strategy is extended to include stresses that are not currently considered. This step is expected to make a clear case for, for example, the inclusion of additional sites for germplasm selection under specific conditions.

Case Studies

Having described our methodology, we now present two case studies: one for upland rice in central Brazil (states of Goiás, Tocantins, Mato Grosso and Rondônia) and another for common beans in the state of Goiás in Brazil. We provide a summary of key results and conclusions. For more detailed descriptions the reader is referred to Heinemann et al. (2015a) for upland rice and Heinemann et al. (2015b) for common beans.

Upland rice in central Brazil

Upland rice (UR) is a key part of the central and northern Brazilian diet, and is the main source of income for many smallholders in the savannah region. The current UR growing area is, however, half of what it was 10 years ago. To an unknown but likely significant extent, these reductions in UR growing area in central Brazil are a product of the UR breeding program strategy, whereby direct grain yield selection is performed primarily under optimal growing conditions. Recent evidence, however, suggests that drought stress conditions are prevalent across central Brazil (Heinemann and Sentelhas 2011), and hence limit the efficiency of the UR breeding program. Here, we hypothesise that the impact of the UR breeding program can be enhanced by better accounting for drought conditions across the UR growing region.

The analysis region comprises the states of Goiás, Tocantins, Mato Grosso and Rondônia (Fig. 2). We gathered data from 17 different experiments conducted at the Embrapa Rice & Beans experimental station in Santo Antonio de Goiás (GO). Six of these experiments were used for calibrating phenology and growth parameters, and the remaining 11 were used for model evaluation. Model calibration experiments included measurements of dates of emergence, flowering, and physiological maturity, as well as of leaf area index and stem, leaf and panicle biomass. Evaluation experiments included only dates of flowering and maturity, and crop yield. We used the crop model Oryza2000 as it has proven to simulate rice yields accurately across a wide range of environmental and management conditions (Bouman and van Laar 2006; Li et al. 2013). Calibration of the model was performed using the built-in genetic algorithm of the Oryza2000 model for the cultivar BRS Primavera –a representative check cultivar for the four states under analysis. For model evaluation, we computed the

RMSE and the Mean Absolute Error (*MAE*). Model calibration and evaluation indicated that the model ably reproduced growth dynamics and crop yield. *RMSE* (*MAE*) values for flowering and maturity dates in the evaluation dataset were 3.56 (2.56) days and 4.47 (4.33) days, respectively, for a ~90-day growing cycle. *RMSE* and *MAE* values for yield were also low (349 and 249 kg ha^{-1}, respectively), and the model also adequately captured the interannual variation in crop yields.

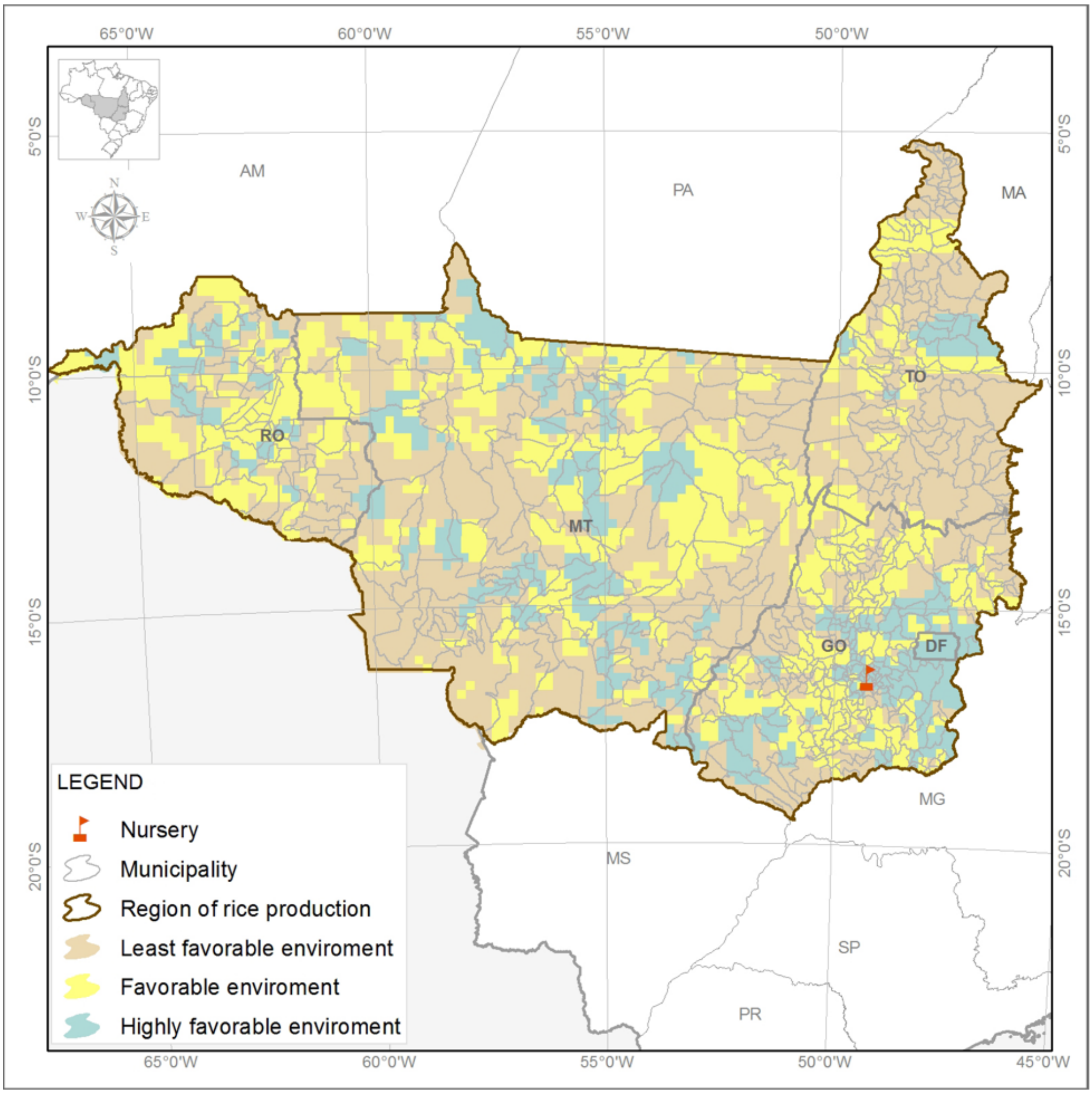

Figure 2 Environmental groups for upland rice in central Brazil. The map shows the the most frequent EG. Blue corresponds to the highly favourable environment (HFE); yellow corresponds to the favourable environment (FE); and beige corresponds to the least favourable environment (LFE).

Spatially-explicit simulations were conducted for 51 weather station zones (defined using Thiessen polygons), 7 soil types (defined based on texture), 8 sowing dates (defined at 10-day intervals from 1st Nov. to 10th Jan.), and 33 years (1980-2012), for cv. BRS Primavera. We then classified the simulated yields using a hierarchical clustering method (Ward 1963), and determined the optimal number of groups using the inertia gain, the within-groups sum of squares, and expert knowledge. Results indicate the existence of three EGs: a highly favourable environment (HFE), a favourable environment (FE), and a least favourable environment (LFE) (Fig. 2). The HFE showed mean yields of 3,168 kg ha^{-1}, and represented 19 % of the production region; the FE presented a mean yield of 2,610 kg ha^{-1} and represented 44 % of the simulated scenarios; and, finally, the LFE showed the lowest yield (1,661 kg ha^{-1}) and represented 37 % of the seasons. The occurrence of HFE was associated with clay soils and early planting dates, whereas the occurrence of LFE was often associated with sandy loam and sandy soils and late planting dates.

Based on our knowledge of the study region, we defined the stress index as the ratio between actual to potential evapotranspiration. In the Oryza2000 model, this factor is used to reduce photosynthesis, and hence is a suitable indicator of drought effects on biomass accumulation and growth dynamics. For each EG we clustered weekly variations in the stress index using the same hierarchical clustering method as that used for determining the EGs. Results indicate the existence of 2 stress patterns for HFE, and 3 stress patterns for both FE and LFE (Fig. 3). For HFE, the two stress patterns correspond to stress-free conditions (69 % occurrence in this EG, profile 1 in Fig. 3) and to terminal drought stress (31 % occurrence in this EG, profile 2 in Fig. 3). For FE, the stress profiles are: [1] reproductive stress (41 % occurrence in this EG); [2] terminal drought stress (40 % occurrence); and [3] severe reproductive stress (19 % occurrence). For LFE, the three stress patterns are much more mixed than for the FE and HFE due to substantial variability as a result of severe drought during almost the entire crop cycle. In this EG, stress profiles are: [1] reproductive (68 %); [2] terminal (14 %); and [3] reproductive-to-grain-filling (17 %).

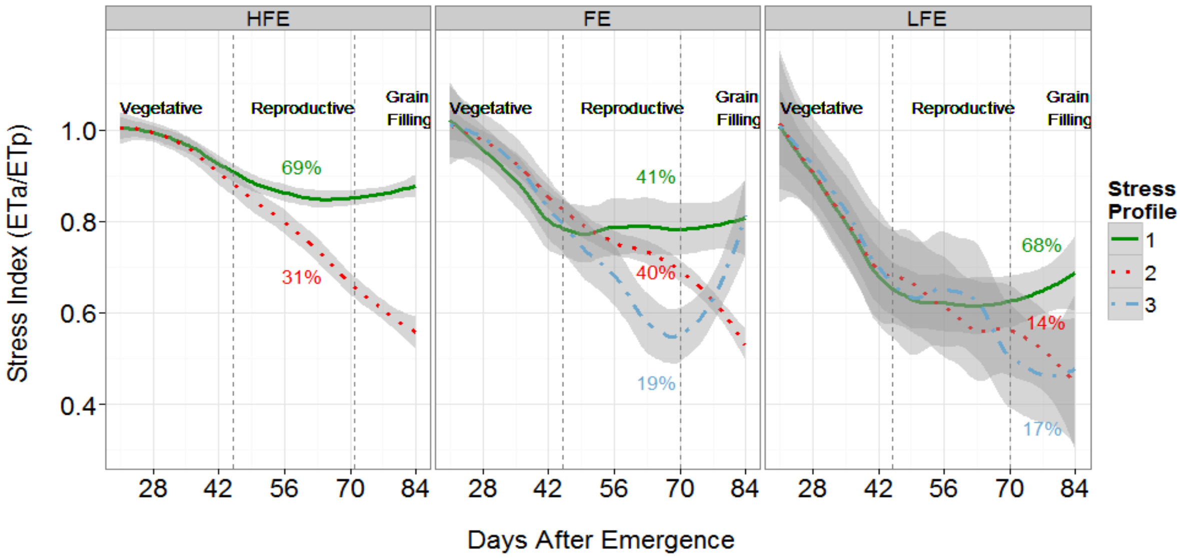

Figure 3 Drought stress patterns for each upland rice EG. HFE: highly favourable environment; FE: favourable environment; and LFE: least favourable environment. Stress types for each environment with numbers representing the frequency of occurrence of stress patterns in EGs. The first and second vertical dashed lines show the average panicle initiation and flowering dates for each environment group, respectively.

The current strategy of the Brazilian UR breeding program is to perform direct selection for grain yield in the best environments. Our results indicate that the strategy of the breeding program should be adjusted as follows:

- In the best environment (HFE, 19 % occurrence), the current strategy is likely to perform well. In Santo Antônio de Goiás (GO) (red flagged point in Fig. 2), where early generation yield testing is performed, HFE shows 62.5% probability of occurrence, suggesting that this site is suitable for selecting for potential yield. Sowing should be undertaken at the beginning of November and in clay soil. Irrigation, however, may be needed in order to avoid stress in certain years.

- In the favourable environment (FE, 44 % occurrence), two distinct stress patterns occur roughly four in every five cropping seasons. One option is to perform selection for wide adaptation to drought, as suggested by Chenu et al. (2011). Another option is to weight the performance of genotypes according to the representativeness of the growing environments where they are tested (i.e. weighted selection).

- For the least favourable environment (LFE, 37 % occurrence), we suggest selection to be specific to high yield under reproductive stress, which is the most likely stress profile in this environment (68 %).

Based on our analyses, we estimate that an additional 42% of coverage (from total) would be possible if breeders were to broaden their selection strategy to select for reproductive stress (which corresponds to 41 and 68% within LFE and FE, respectively). This amounts to a four-fold increase in the coverage of the UR breeding program, which we argue is likely to be cost effective. Realising this potential, however, will ultimately depend on the existence and efficiency of seed systems, and on the adoption barriers to new germplasm.

Comon beans in Goiás, Brazil

Brazil is the largest producer and consumer of common bean (*Phaseolus vulgaris* L.) (FAO 2014). In the state of Goiás (a large bean producer in Brazil), crop production occurs in three growing seasons or `*safras*`. A first season (wet season), for which sowing occurs between 1st Nov. and 31st Dec.; a second season (dry season), for which sowing occurs between 1st Jan. and 28th Feb.; and a third season (winter season) for which sowing occurs from 1st May to 30th Jun. Both the dry and wet seasons are rainfed, whereas the winter season is irrigated. The difference in planting times and yields between seasons implies the occurrence of different types of stress across time and space. Major limitations in the wet and dry seasons are low soil fertility, drought, nitrogen deficiency due to poor nitrogen fixation, as well as several bacterial, fungal and viral diseases (Beebe et al. 2011; Souza et al. 2013; Araújo et al. 2015). The Brazilian common bean breeding program, led by Embrapa's Rice and Beans unit, focuses on developing germplasm with broad adaptation for all Brazilian bean production regions. In their scheme, the early generation screening yield trials (nursery) are always performed in the winter season under well-watered conditions (i.e. fully irrigated). Although this is a cost-effective strategy, the main caveat is that it increases the risk of developing genotypes that do not respond well under stress. We analyse drought stress patterns in the rainfed (wet and dry) seasons in order to determine the extent to which the current strategy of the common bean breeding program needs to be adjusted to include drought stress conditions.

As stated above, we concentrate on the state of Goiás (Fig. 4), for both wet and dry seasons. We assembled a large database of field experiments (41 in total) for two cultivars: cv. Pérola (31 experiments) and BRS Radiante (25 experiments). Measured variables varied across experiments but in general included sowing, flowering, first pod, first seed, and physiological maturity dates, leaf, stem and pod biomass, leaf area index and yield. Most experiments were conducted in Santo Antonio de Goiás (GO), but 14 of them were multi-site trials conducted in different locations. Five out of the 41 experiments were used for model calibration, whereas the remaining 36 experiments were used for model evaluation. We used the widely tested crop model CSM-CROPGRO-DRYBEAN (Boote et al. 1998) from the Decision Support System for Agrotechnology Transfer version 4.5 (Jones et al. 2003). Model calibration was performed following Alderman et al. (2015), who adopt a Markov Chain Monte Carlo approach and the Metropolis Hastings algorithm for parameter estimation. The CSM-CROPGRO-DRYBEAN model showed acceptable performance for both cultivars in simulating end of season yield and phenology, with most simulated quantities within a 95 % confidence interval derived from observations. The model also captured well the seasonal variations in dry matter dynamics, leaf area index and soil moisture under moderate drought, but was unable to adequately simulate severe drought conditions. To our knowledge, however, severe drought only rarely occurs in the wet and dry seasons. Multi-environment simulations also showed good agreement with observations, with *RMSE* (*MAE*) values for Radiante and Pérola being 404 (328) and 322 (319) kg ha^{-1}, respectively.

Simulations were conducted for the period 1980-2013 for 26 weather station regions (defined using Thiessen polygons), for 3 soil types (oxisol, ultisol, inceptisol), and for a total of 13 sowing dates (defined at 10-d intervals from 1st Nov to 30th Dec for the wet season, and from 10th Jan to 28th Feb for the dry season) for the two cultivars (Pérola and BRS Radiante). Clustering of yields and determination of the number of EGs was undertaken as it was for upland rice. Fig. 4 shows the EGs for both seasons.

For the wet season, results indicate the existence of two markedly different EGs: a highly favourable environment (HFEw, 44 % occurrence) and a favourable environment (FEw, 56 % occurrence) (Fig. 4, top maps). The HFEw has an average simulated yield of 3,655 kg ha^{-1}, whereas the FEw has an average simulated yield of 2,870 kg ha^{-1}. For the dry season (Fig. 4, bottom maps), we also find two EGs: highly favourable environment (HFEd, 58 % occurrence) and favourable environment (FEd, 42 % occurrence). Yields in HFEd were

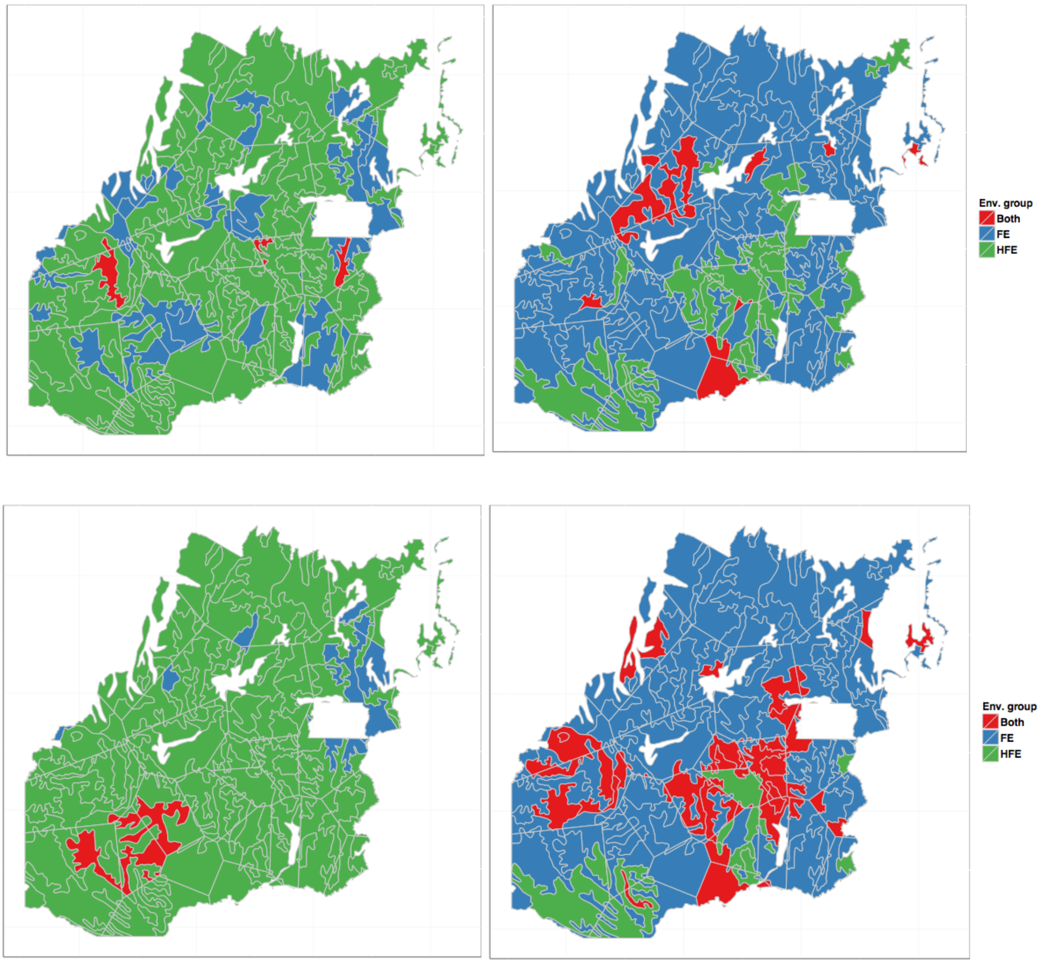

Figure 4 Environmental groups for the dry bean wet (top maps) and dry (bottom maps) seasons in Goiás, Brazil. The maps on the left show the most frequent EG for early planting (i.e. during Nov. for the wet season and during Jan. for the dry season), and the maps on the right show the most frequent EG for late planting (i.e. during Dec. for the wet season and Feb. for the dry season).

roughly twice as large as in FEd (i.e. 2,781 vs. 1,356 kg ha^{-1}). For both seasons, the occurrence of the different EGs was strongly associated to the sowing date, with early sowing dates showing a high likelihood of HFEw and HFEd, and late sowing dates showing a high likelihood of FEw and FEd.

The five-day mean values of the water stress index (WSPD) – a photosynthesis reduction factor, derived by calculating the ratio of actual to potential transpiration, were used to determine drought stress profiles for each environment and season. Results are shown in Fig. 5.

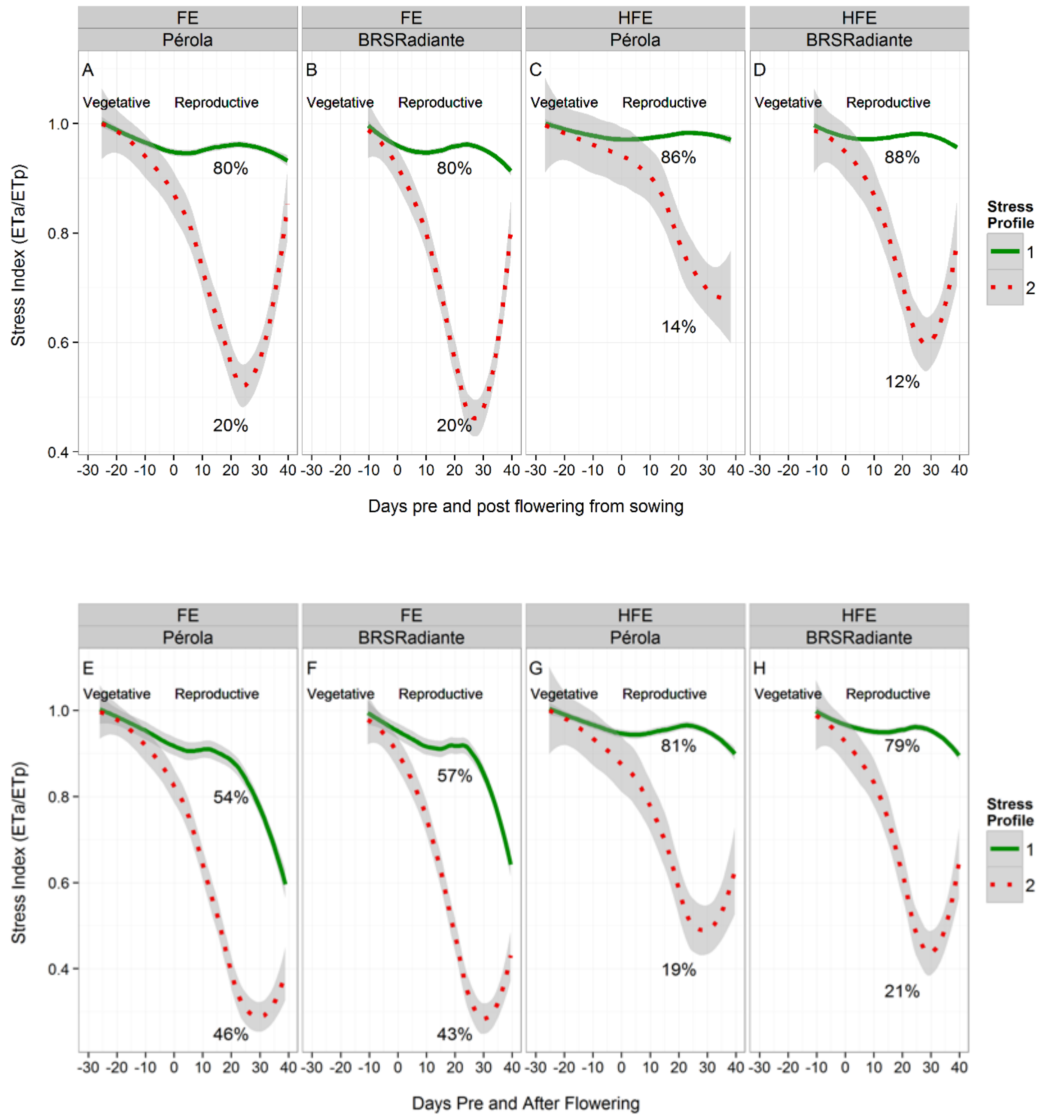

Figure 5 Drought stress patterns for favourable environment (FE) and highly favourable environment (HFE) for wet (top) and dry (bottom) common beans growing seasons. Legend indicates stress types for each environment and numbers within the panels represent the frequency of occurrence of stress patterns in each EG. Grey bands represent the 95% confidence interval around the average stress patterns. Stress Profile Legend: 1 – drought free profile; 2 –reproductive terminal drought stress (A, B, C and D); 1 –terminal drought stress (E, F); 1 – stress-free (G; H); and 2 –reproductive-terminal drought stress (E, F, G, H).

For the wet season, two stress profiles exist for the highly favourable environment (HFEw). Namely, stress-free (pattern 1 in top panel of Fig. 5, 86-88 % occurrence depending on cultivar) and terminal-reproductive stress (pattern 2 in top panel of Fig. 5, 12-14 % depending on cultivar). For FEw, stress-free conditions (pattern 1) are also the most frequent with 80 % occurrence for both cultivars, whereas terminal-reproductive drought stress (pattern 2) occurs only 20 % of the time, though it causes a yield reduction of 68-74 % in relation to stress-free conditions. For the dry season, HFEd consists of two stress profiles: [1] stress-free conditions, which occur 79-80 % of the time depending on the cultivar; and [2] terminal-reproductive drought stress, which occurs 20-21 % of the time depending on the cultivar. For FEd, we find that terminal drought stress (pattern 1) represents 56-62 % of conditions, whereas terminal-reproductive drought stress represents 44-58 % of conditions.

Our analyses suggest that in the rainfed seasons, drought-stress conditions occur about 25 % of the time for both cultivars Pérola and BRS Radiante. For the common bean breeding program, a 25 % frequency of occurrence of moderate drought means that germplasm selection under drought conditions may not be warranted. However, we note that, particularly in the dry season, yield reductions from drought can be above 50 % compared to stress-free conditions. Therefore, we argue that it may be desirable to include drought response as part of the selection criteria. We also suggest that further research be conducted to identify other stresses that cause yield reductions in the wet and dry seasons in relation to the winter season. Once these stresses are known, the common bean breeding program should adapt their selection practices accordingly so as to be able to develop genotypes that are more suitable for these environments.

A web platform to visualise and integrate results

We developed a web application to visualise the results of the application of this approach to different crops and regions: http://www.ccafs-tpe.org (Fig. 6). The tool consists of three main components:

- A map application to visualise spatially explicit environmental groups, to query daily weather data and soil data, as well as to visualise dynamic graphs of yield variation and of stress profiles.
- Case studies and applications providing summaries and key findings of the analyses we have conducted so far. These include: upland rice in Brazil, dry bean in central Brazil, and irrigated rice in Colombia. Additionally, we blog about papers that use methods akin to ours.
- Documentation and data downloads: we provide detailed information on our methodology and results of our case studies, including free versions of published journal articles, reports and tutorials. We also allow users to download our project input and output data.

Figure 6 CCAFS Target Population of Environments web platform at http://www.ccafs-tpe.org

Finally, we encourage other researchers to get involved in our project by providing data and/or results of the application of methods that are akin to ours.

Conclusions and future work

As part of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), we implemented a project named *Target Population of Environments* (TPE). We developed a methodology to classify environments and to determine stress profiles within these environments. Our results for upland rice in central Brazil suggest that breeding should be adjusted to include selection under drought conditions. On the other hand, results for common bean in the state of Goiás (Brazil) suggest that drought stress does not occur with enough frequency so as to warrant selection under drought conditions. However, for beans, we note that differences in observed farmer yields between seasons (wet, dry and winter) suggest that there may be other stresses acting to reduce yields. Future work should focus on identifying and characterising such stresses.

The priorities identified by our analyses correspond to current climates, and, while they serve to identify clear priorities where breeding gains are necessary presently, climate change may imply shifts in some of these priorities [e.g. Lobell et al. (2015)]. As an obvious next step in this project, we are conducting analyses for upland rice and common beans in Brazil where we quantify changes in stress patterns under future climates. We are also extending the analyses to rice in sub-Saharan Africa, and flooded rice in southern Brazil.

Finally, we wish to remark that other methods exist that classify environments for breeding. Many of these have been successful to orient crop improvement strategies in the last two or three decades (Hodson et al. 2002; Ortiz et al. 2008; Cairns et al. 2013). Future work should also focus on identifying how different approaches to environmental grouping can be used together to improve breeding practice.

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