

# Comparing empirical and survey-based yield forecasts in a dryland agro-ecosystem

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## ABSTRACT

Accurate crop yield forecasts before harvest are crucial for providing early warning of agricultural losses, so that policy-makers can take steps to minimize hunger risk. Within-season surveys of farmers' end-of-season harvest expectations are one important method governments use to develop yield forecasts. Survey-based methods have two potential limitations whose effects are poorly understood. First, survey-based forecasts may be subject to errors and biases in the response data. For example, the weather variables that most impact yields may not be the same as those that farmers consider when shaping their yield expectations, thereby undermining forecast accuracy. Secondly, surveys are typically conducted late in the growing season, giving the government less advance notices of potential crop failures or low yields, and are costly to implement. Here we investigate these limitations within the context of Zambia's annual Crop Forecast Survey (CFS). Concerning the first limitation, we analyzed the differences between CFS-predicted yields and reported yields collected by Post Harvest Surveys, and found that excess rainfall during the planting stage was more important to the actual yield than to farmers' yield forecasts. For the second limitation, we evaluated whether a simple empirical yield forecast model could produce earlier and more accurate yield forecasts than the CFS. A random forest model using weather variables, soil texture, and soil pH as predictors were able to produce yield forecasts at the same or higher accuracy since the planting season.

## 1. Introduction

Agriculture is vital to Sub-Saharan African economies, averaging 17.2% of GDP in 2015 (Agriculture, 2018). Agriculture also provides the primary livelihood for a majority proportion of the region's populations (Burney et al., 2013; Rockström, 2000). Agriculture is expected to expand dramatically to meet the region's rapidly growing food demands (Searchinger et al., 2015), and small to medium farmers are expected to play a critical role in this expansion (Morris and Byerlee, 2009; Jayne et al., 2016).

This agricultural dependence makes the region's economies, as well as the food security of many households, highly vulnerable to climate

risk. This risk is further exacerbated by two factors: 1) the vast majority of farms in Sub Saharan Africa (SSA) are rain-fed (Burney et al., 2013), with relatively limited prospects for significant irrigation expansion (You et al., 2011); 2) most crops are produced in savanna regions, which are characterized by strong rainfall seasonality that exhibits pronounced and increasing variability at both inter- and intra-annual scales (Falkenmark and Rockström, 2008; Verdin et al., 2005a; Gaughan and Waylen, 2012; Nicholson, 2000; Rowhani et al., 2011; Milgroom and Giller, 2013). Seasonality limits the number of crops that can be grown during the year, while variability can lead to crop failure during the rainy months when crops are grown. For example, within-season variability of precipitation intensity and frequency can have

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large impacts on maize, rice and sorghum yields (Cabas et al., 2010; Guan et al., 2015; Rowhani et al., 2011).

In addition to rainfall variability, temperature extremes pose a substantial threat to food security. Previous work has shown that maize (Africa's most widely grown staple crop, accounting for 30% of planted area; Cairns et al., 2013) is globally sensitive to elevated temperatures (Lobell and Field, 2007), and African maize yields may be reduced by  $\geq 1\%$  for each degree day above  $30^\circ\text{C}$  (Lobell et al., 2011).

Given SSA's strong dependence on agriculture, the region's susceptibility to climate variability and extremes, and the sensitivity of one of its main crops to these extremes, the ability to forecast the potential impacts of extreme weather on maize harvests is crucial to mitigating yield loss and the attendant risks to livelihoods. Two types of forecasts are important in this regard, the first being pre-season forecasts of expected growing season weather conditions, and the second being yield forecasts, which are made during the middle or second half of the growing season. Pre-season weather forecasts allow governments to inform farmers of potential extreme conditions, so that they can alter their management practices to mitigate losses (Ingram et al., 2002; Patt et al., 2005; Roncoli et al., 2009). Yield forecasts allow governments to anticipate changes in food supply before the end of the growing season, and thereby implement compensatory policies (e.g. increased trade or price stabilization mechanisms) that help to buffer production and price shocks to ensure food remains available and accessible (Dorosh et al., 2009; Mason and Myers, 2013; Minot, 2014). It follows that the accuracy of both weather and yield forecasts are essential for maintaining food security.

Two standard methods employed for yield forecasts are: (1) remote sensing-based yield prediction, (2) yield forecasts developed from representative surveys of farming households, in which farmers' report their expectations of the final harvest and their planted areas. Satellite-based methods are widely used throughout sub-Saharan Africa, and are typically based on drought and Vegetation Indices that are combined with models to forecast yields (Brown et al., 2007; Rojas et al., 2011; Verdin et al., 2005b). The challenge behind using such methods is that the accuracy of many of the necessary remote sensing inputs such as land cover maps can exacerbate uncertainties (Estes et al., 2018) inherent in forecasting.

Zambia is an example of a country that relies on the survey-based approach, one that also demonstrates how the results of this approach can have significant policy ramifications. During March of each year, Zambia's Central Statistical Office (a division of the Ministry of Agriculture and Livestock) conducts Crop Forecast Surveys (CFS). The CFS collects data on end of season harvests (measured in total kg or bags of crop) expected by representative farming households, as well as the total area that the farmer reported as being planted to the crop. These surveys are followed by year-end Post-Harvest Surveys (PHS) during which the actual harvest numbers are collected from the same households. The intention of the CFS and PHS is that the PHS is a revisit of the CFS households. However, enumerators do not always find the exact same households in 100% of cases and the exact proportion of the matches between CFS and PHS households is unknown. The CFS is used to construct national-level predictions of the season's total harvest, which is used by Zambia's Food Reserve Agency (FRA) to implement policies that aim to supply sufficient food and to maintain price stability. For example, during normal harvest years the FRA purchases maize from small-holders at above-market prices to encourage production. In contrast, during low harvest years, the FRA imports maize to sell to domestic millers at below-market rates (Mason and Myers, 2013).

Numerous potential sources of error in farmer-reported yield forecasts exist. Firstly, farmers may lack the skill or knowledge required to estimate yields before harvest, thereby introducing potential bias or error into the CFS. As one example, farmers may make their predictions by evaluating certain weather events that have less impact on final yield than other factors. Secondly, even if a farmer is skilled in predicting yield and bases this prediction on the right variables, events

following the forecast date (e.g. pest, disease, or extreme weather events) may significantly impact yield.

Another potential shortcoming of a survey-based method such as the CFS is the relatively late timing of the resulting yield forecast, which reduces the lead time for policy-makers to respond. In addition, the survey-based approach is also expensive and time-consuming to implement.

Given its importance to the Zambian food security policy, both the potential errors and the late timing of the CFS could have substantial socio-economic consequences. As an example, an overestimate of total harvest from the CFS could lead to inadequate maize importation in a low-harvest year, leading to domestic food price spikes. Despite such potential consequences, the errors and biases in the CFS are not well-understood, nor are their potential causes. It is also unclear whether reliable yield forecasts can be obtained for less cost and earlier in the season. To our knowledge, no one has directly compared survey-based forecasts with other methods.

In this study, we set out to address these knowledge gaps. To examine the degree of error in the CFS and its potential causes, we first quantified the discrepancies between the estimated and actual yields from Zambia's crop forecast surveys (CFS) and post-harvest survey (PHS). We then used empirical models to identify the weather and soil variables that have the most significant influence in explaining variation in both the CFS and PHS yields, to evaluate whether farmers' predictions are informed by different variables than those most strongly correlated with final yield. We also examined whether post-survey weather impacts PHS yields, thereby contributing to CFS prediction error. Lastly, to investigate whether alternative methods could provide reliable forecasts at earlier points in the season, we evaluated whether an empirical agro-meteorological forecast model, trained with weather data from different points in the growing season, could predict end-of-season yields earlier and more effectively than CFS.

Our results provide valuable insights into yield forecasting methods that may be useful for helping to improve food security monitoring systems.

## 2. Methods

### 2.1. Study site

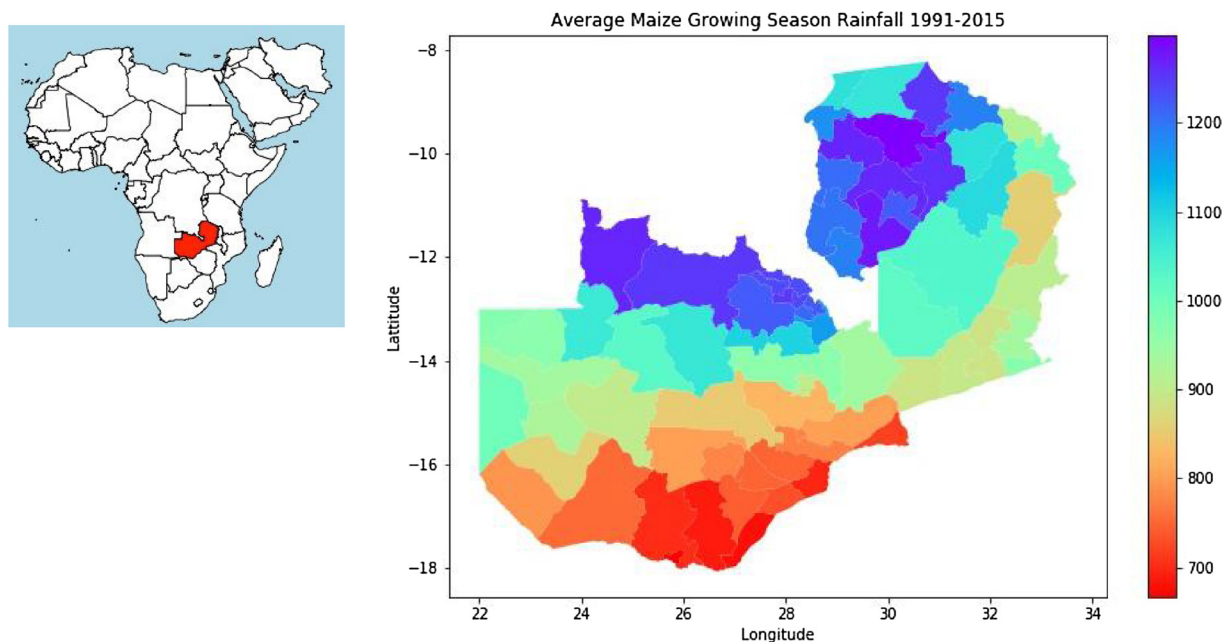
Zambia is a landlocked country in sub-Saharan Africa with a semi-arid subtropical climate (Fig. 1). Maize is the most widely planted and consumed staple crop in Zambia, and is primarily grown under rain-fed conditions (Mason and Myers, 2013) during a single growing season from November to May. Total rainfall ranges from approximately 700 mm in the South of the country to 1400 mm in the North (Fig. 1). The southwestern part of Zambia is especially dry.

In addition to these characteristics, Zambia is a useful case study because it is broadly representative of the larger region. From a socioeconomic perspective, Zambia's smallholder-driven agricultural sector is a primary source of livelihood for much of the population, as with many other SSA countries (Rockström, 2000). It is also situated within the belt of higher rainfall savannas that comprise much of Africa's landmass, one where smallholder farmers are expected to be a key part of agricultural development in the coming decades (Searchinger et al., 2015; Morris and Byerlee, 2009).

### 2.2. Data

#### 2.2.1. Survey data

The Zambian government conducts a Crop Forecast Survey (CFS) in mid-March, two to three months after planting, and approximately two months before maize harvest. It then conducts a Post-Harvest Survey (PHS) in October or November following each growing season. We obtained CFS survey data for the time periods of 2001–2005, 2008–2014, and PHS survey data from 1991 to 2005, 2007, 2008, 2011



**Fig. 1.** Map of Africa with Zambia highlighted in red and the total rainfall (mm) in the rainy season from October to June spatially averaged by district and then averaged across 1991 to 2015.

and 2012. The CFS and PHS were collected at a sub district level of Sample Enumeration Area (SEA), but the SEA boundaries change over time, therefore we aggregated the survey data to the district scale for our analyses. Because we are studying the difference between farmers' yield forecasts and their actual yield, we confined our analyses to the years in which the two datasets intersected (2001–2005, 2008, 2011, and 2012). After initial inspection, we removed the 2002 datasets from our analysis, as the CFS in that year contained yield values ranging from zero to 70 kg/ha (50–100 times smaller than the corresponding PHS), suggesting an error of data entry or units. We also removed the 2008 dataset, which was missing data for 60% of the districts. From the remaining datasets, we removed all districts containing any years with missing values, leaving us with a balanced panel dataset containing CFS and PHS yield data for 70 districts for the years 2001, 2003–2005, 2011, and 2012. We computed the difference between CFS and PHS yields as a third response variable in our analyses.

### 2.2.2. Explanatory variables

We used Climate Hazards Group Infra-Red Precipitation with Stations (CHIRPS) satellite based precipitation data (Funk et al., 2015) and temperature data from the Princeton Global Forcing (PGF) dataset (Sheffield et al., 2013, 2006). Although station-collected weather observations are preferable to satellite-based reanalysis data, there are very few publicly available station records for Zambia. If we relied on station data only, we would have been limited to using a few points to represent weather for all of Zambia, which would be inadequate to represent the high spatial variability of weather conditions between districts. The CHIRPS dataset has a quasi-global coverage from 1981 to present with 5km-daily resolution. CHIRPS combines satellite imagery and station data to create a bias-corrected gridded rainfall time series for trend analysis. Although rainfall station data are sparse in Zambia, the CHIRPS dataset performs better than coarser satellite-derived and gauged corrected rainfall products (Beck et al., 2017). Nonetheless, the high spatial resolution of CHIRPS captures rainfall spatial variability and land heterogeneity (Musau et al., 2016). The temperature dataset is based on the global, 0.25°, 3-hourly PGF dataset (Sheffield et al., 2006), which was constructed by blending reanalysis data with several observational datasets. The reanalysis temperature data are adjusted to match the monthly mean daily average and diurnal range of

temperature from the CRU TS3.24.01 dataset (Harris et al., 2014), which is a global gridded analysis of available station data, including empirical estimates where stations are sparse. We spatially disaggregated the PGF temperature data to 0.05° for Zambia with account for elevation differences, for the period 1980–2015. We did not integrate station data directly into the analysis because only one station is available from readily available databases, such as the U.S. National Oceanic and Atmospheric Administration (NOAA) Global Surface Summary of the Day database (GSODI) (see Fig. 1, Ceccherini et al., 2017). We aggregated the weather variables from daily to monthly time steps for each district and each year: first aggregating across days in a given month for all pixels of a district and then taking a spatial average across all pixels of a district. For precipitation, we calculated the monthly sums (in mm) for each ~5 km pixel and averaged these sums across the pixels for each district,

$$P_{it} = \frac{1}{N_i} \sum_k P_{itk} \quad (1)$$

Where  $i$  represents an index for the districts,  $t$  represents an index for a month in a year,  $N$  represents the total number of pixels in a district, and  $k$  represents an index for the pixels within a particular district, and  $P_{itk}$  represents the total precipitation of pixel  $k$  in month  $t$  of this particular year.

We aggregated the monthly average of daily temperature ( $T_{max}$  and  $T_{min}$ ) through the following computation, denoted as  $Temp_{it}$ , is as follows:

$$Temp_{it} = \frac{1}{N_i} \frac{1}{D_t} \sum_k \sum_d T_{itdk} \quad (2)$$

Where  $T_{itk}$  is either the maximum or minimum temperature of pixel  $k$  on day  $d$  in month  $t$  of a particular year, and  $D$  is the total number of days in a month.

We also computed indicators of extreme weather condition, namely drought and flooding. The longest number of consecutive dry days in a month is indicative of the drought condition ( $L_{it}$ ),

$$L_{it} = \frac{1}{N_i} \sum_k l_{itk} \quad (3)$$

Where  $l_{itk}$  is the maximum number of consecutive dry days in pixel  $k$  in month  $t$  of a particular year. Excessive rainfall was estimated using the

sum of daily precipitation exceeding 10 mm, which was the 90th percentile of all CHIRPS pixels' daily rainfall from 1981 to 2015,

$$A_{it} = \frac{1}{N_i} \frac{1}{D_t} \sum_k \sum_d (p_{idk} - 10) \quad (4)$$

where  $d$  indexes for the day of month  $t$ ,  $D_t$  is the total number of days in month  $t$ , and  $A_{it}$  represents the accumulated extreme rainfall of district  $i$  in month  $t$  of a particular year.

We summarized all the variables in Table 1, and their descriptive statistics in Table A1 in the Appendix A.

## 2.3. Analysis

### 2.3.1. Effectiveness of CFS as a predictor of PHS

To quantify the accuracy of the CFS in forecasting final yields, we calculated the root mean square error between CFS and PHS yields for each district and year. We also used paired  $t$ -test to test for differences between the mean CFS and PHS yields, as well as the Pearson correlation coefficient to assess the strength of correlations between CFS and PHS yields.

### 2.3.2. Linear panel data analysis

To assess the factors driving variations of yield estimates from the CFS, PHS and their difference, we undertook panel regression analyses with district-level random effects ("splm" package in R).<sup>1</sup> Since both weather data and yield data tend to be spatially correlated, we tested for potential spatial autocorrelation among districts for each year using both semi-variogram by distance among districts and the Moran's  $I$  test. The result showed that there was significant spatial autocorrelation in yields and expected yields in all years of the PHS dataset, and 4 out of 7 years in the CFS dataset. The predictor variables also showed significant spatial autocorrelation. We therefore employed a general panel model that included a spatial lag of the dependent variables and spatial autoregressive disturbances. We tested the residuals of the fitted model for each single year using Moran's  $I$  test for spatial autocorrelation, which showed no significant spatial autocorrelation ( $p > 0.8$  for all cases).

The Hausman test showed that random effects models were preferred compared to district fixed effect and year fixed effect models. Forward stepwise selection was used to select features to find the best model for explaining variation in CFS and PHS yield estimates. Interaction terms between precipitation and temperature of each month were included in the model selection process. To test the effects of weather during different periods of the growing season, we developed several sets of models in which we progressively added weather variables from the beginning of the season up until the end. The panel model was run with the best-selected model of predictors from October to the specific ending to a threshold month, in addition to soil condition variables. In other words, we maximized the total amount of variation in CFS and PHS yield explained by weather variables from October to a month in the middle of the growing season (Table 2). For example, Model\_1 regressed yield on October weather variables and soil condition predictors, Model\_2 regressed yield on October and November weather variables and soil condition predictors, Model\_3 included weather variables from October through December and soil condition predictors, etc. This approach allowed us to assess the marginal information gained, by adding weather observations from each additional month, in terms of explaining farmers' yield forecasts as well as the actual yield from weather observations of each additional month during the growing season in explaining farmers' yield forecasts as well as the actual yield.

<sup>1</sup> Giovanni Millo, Gianfranco Piras (2012). splm: Spatial Panel Data Models in R. Journal of Statistical Software, 47 (1), 1–38. URL <http://www.jstatsoft.org/v47/i01/>.

### 2.3.3. Machine learning-based yield forecasts

The CFS is a labor-intensive way of predicting yield, thus it is useful to know whether other less expensive approaches can be used to provide the same (or better) predictive performance. To undertake this assessment, we developed an empirical forecast model of final yield using the Extreme Gradient Boost (XGBoost) regression tree ensemble method together with simple weather and soil variables as predictors. The benefit of a non-parametric regression tree-based method is that it captures all non-linear relationships between yield and various contributing factors (Lobell et al., 2005; Miao et al., 2006; Titttonell et al., 2008; Zheng et al., 2009; Dai et al., 2011). The drawback is that each individual node or data split in the tree is highly sensitive to the sample of data (Hastie et al., 2009). Aggregating over hundreds of regression trees on bootstrapped data relieves the high variance problem of regression trees, and the correlation among trees is reduced by also randomly selecting from predictor variables in a Random Forest algorithm (Hastie et al., 2009). XGBoost is an upgraded version of Random Forest that also optimizes for the maximum depth of each regression tree. We thus used cross-validation to optimize the depth of the regression tree, which was seven. Similar to the forward selection by month in the spatial panel model method described above, we tested alternative versions of XGBoost that incrementally added weather variables from October through March, in addition to the soil predictors.

We fit and evaluated models using a leave-one-out (LOO) cross validation approach, in which each model was trained on all but one year's worth of data. We evaluated model skill based on the RMSE between the PHS and model-predicted yields for both the training years and the excluded year, which was used to test the performance of the fitted model. This LOO procedure was repeated for all study years (2001, 2003–2005, 2008, 2011, 2012), and the average RMSE as well as the standard deviation of both testing set and training set was computed.

## 3. Results

### 3.1. CFS as a predictor of PHS

The district level CFS and PHS yields both had a normal distribution. The mean PHS yield was 1847 kg/ha with a standard deviation of 720 kg/ha, while the CFS yield averaged 2102 kg/ha with a standard deviation of 1142 kg/ha. An F-test applied to the variances of PHS and CFS showed that CFS had a variance that was significantly larger than PHS ( $p < 0.0001$ ), therefore we used a paired  $t$ -test that assumed different variances between pairs to evaluate mean differences. This test showed that the CFS mean was significantly higher than that of PHS (1-sided test  $p < 0.0001$ ,  $df = 511$ ; Fig. 2), but there was a strong positive correlation between both datasets (Pearson's  $r = 0.9$ ).

### 3.2. Panel model to understand key factors influencing CFS and PHS

To identify the factors driving variations in both the CFS and PHS and how these differed between the two datasets, we undertook two separate analyses with the spatial panel models. First, we assessed the differences in which variables were selected by each model. Secondly, in the case of shared variables, we evaluated the differences in the corresponding significance levels and magnitudes of the coefficients.

The first assessment showed that the models for both the CFS and PHS selected the same weather variables representing the same months (Table 2). We did not use polynomial terms to allow for simple interpretations of the coefficients. Among the soil property measures, soil texture was the only variable selected as significant. The similarity between the two models suggested that the discrepancies between CFS yield forecasts and PHS reported yields was not attributable to differences in what farmers understood to be the important drivers of yield, and what the actual drivers were; if there was such a difference, we

**Table 1**

A summary of the details of the response and predictor variables, including their category, variable name, unit and literature sources either as the data source or justifications for our computations. To assess the progression of increased prediction accuracy of yield from the added weather observations of each additional month in the growing season, all the weather indicators were computed at monthly time step.

| Category                                                  | Variable Acronym                                  | Variable Unit           | Description                                                                                                                                                                                                                                                                           | Source                                                                        |
|-----------------------------------------------------------|---------------------------------------------------|-------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| Response (2001, 2002, 2004, 2005, 2007, 2008, 2011, 2012) | CFS (n = 420)<br>PHS (n = 490)<br>Diffy (n = 420) | kg/ha<br>kg/ha<br>kg/ha | (CFS – PHS)                                                                                                                                                                                                                                                                           | Central Statistical Office in Ministry of Agriculture and Livestock of Zambia |
| Biophysical                                               | SoilTexture                                       | –                       | Soil parent material categories (ordered by increasing clay and decreasing sand level): sandy (n = 11); course loamy (1); course- find loamy (6); fine loamy - clay (36); clay- fine loamy (4), clay (12)                                                                             | Zambia Government, year unknown, maybe 1970s                                  |
|                                                           | SoilDrain                                         | –                       | Soil drainage level: excessively (n = 11), excessive-well (6), well (48), imperfect (2), poor (1), very poor (2)                                                                                                                                                                      |                                                                               |
| Precipitation                                             | SoilpH                                            |                         | Aggregated pixel level soil pH data from the soilgrid.org                                                                                                                                                                                                                             |                                                                               |
|                                                           | OctPrec                                           | mm                      | Monthly total precipitation first aggregated to individual pixel and then averaged across individual district-year. Precipitation data came from CHIRPS at 0.05 degree resolution product. For a harvest season in year y, October to December precipitation data came from year y-1. |                                                                               |
|                                                           | NovPrec                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | DecPrec                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | JanPrec                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | FebPrec                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | MarPrec                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | OctDry                                            | days                    | The longest consecutive dry days in a month. A dry day is defined as having rainfall lower than 0.1 mm.                                                                                                                                                                               | (Sillmann et al., 2013)                                                       |
|                                                           | NovDry                                            |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | DecDry                                            |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | JanDry                                            |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | FebDry                                            |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | MarDry                                            |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | OctAccum10                                        | mm                      | The sum of daily precipitation that is above 10 mm.                                                                                                                                                                                                                                   | (Urban et al., 2015; Sillmann et al., 2013)                                   |
|                                                           | NovAccum10                                        |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | DecAccum10                                        |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | JanAccum10                                        |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | FebAccum10                                        |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | MarAccum10                                        |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
| Temperature                                               | OctTemp                                           | °C                      | Average monthly temperature for each district year.                                                                                                                                                                                                                                   | (Abraha and Savage, 2006; Lobell et al., 2013; Nicholson, 2000)               |
|                                                           | NovTemp                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | DecTemp                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | JanTemp                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | FebTemp                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | MarTemp                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | OctTmax                                           |                         | Average of daily maximum and Average of daily minimum temperature for each district year by month.                                                                                                                                                                                    |                                                                               |
|                                                           | NovTmax                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | DecTmax                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | JanTmax                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | FebTmax                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | MarTmax                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | OctTmin                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | NovTmin                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | DecTmin                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | JanTmin                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | FebTmin                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |
|                                                           | MarTmin                                           |                         |                                                                                                                                                                                                                                                                                       |                                                                               |

**Table 2**

Selected PHS and CFS model by threshold month. CFS column is empty when the same as PHS model, and differences in the two models are highlighted in bold.

| Threshold Month | PHS Model                                                                                                 | CFS Model                                                                                       |
|-----------------|-----------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| October         | Yield ~ SoilTexture + OctPrec                                                                             |                                                                                                 |
| November        | Yield ~ SoilTexture + OctPrec +<br>NovPrec + NovTmin                                                      |                                                                                                 |
| December        | Yield ~ SoilTexture + OctPrec +<br>NovPrec + NovTmin + DecAccum10 * DecTmin                               | Yield ~ SoilTexture + OctPrec + NovAccum10 + NovTmin + DecAccum10 + DecTmin                     |
| January         | Yield ~ SoilTexture + OctPrec +<br>NovPrec + NovTmin + DecAccum10 * DecTmin<br>+ JanTmin                  |                                                                                                 |
| February        | Yield ~ SoilTexture + OctPrec +<br>NovPrec + NovTmin + DecAccum10 * DecTmin<br>+ JanTmin + FebAccum10     | Yield ~ SoilTexture + OctPrec +<br>NovPrec + NovTmin + DecAccum10 + DecTmin + FebPrec + FebTmax |
| March           | Yield ~ SoilTexture + OctPrec +<br>NovPrec + NovTmin + DecAccum10 + DecTmin + FebPrec + FebTmax + MarTmax |                                                                                                 |

would expect the CFS model to select different variables.

For the second assessment, we compared the CFS and PHS models that used weather variables from October to March. A total of 62.3% of variation in the PHS yields and 49.6% of the CFS yields were explained

by their respective models (Fig. 3). The majority of predictor variables showed the same direction of influence on yield when they were statistically significant ( $p < 0.05$  level). For instance, sandy soil had the lowest yield among all soil types, followed by clay to fine loamy soil,

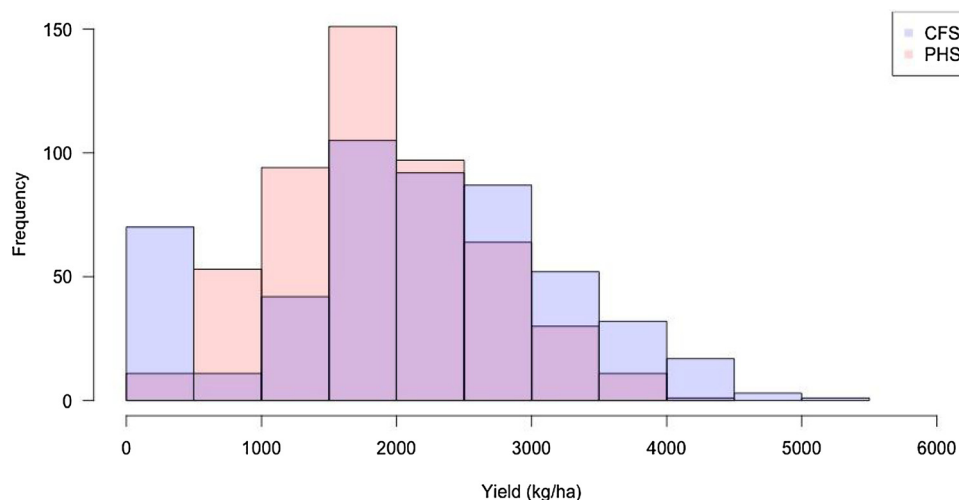


Fig. 2. Histogram of Crop Forecast Survey (CFS) and Post Harvest Survey (PHS) yield.

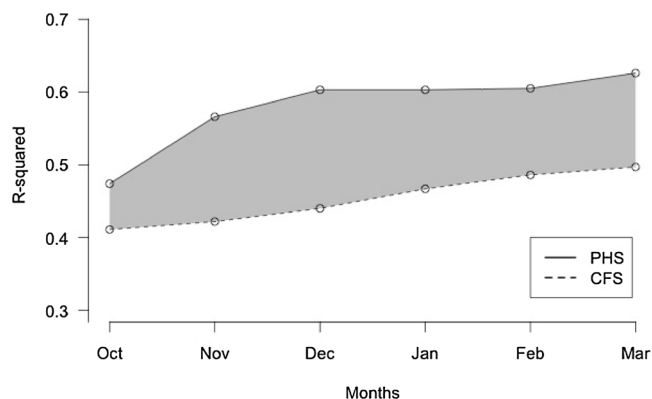


Fig. 3. The amount of variance in CFS and PHS explained by the weather variable from October to a threshold month were shown in the dotted and solid black lines. The grey area highlights the magnitude of difference in the coefficient of determination ( $R^2$ ).

across both models. The temperature and precipitation variables in both models had the same signs (OctPrec, NovAccum10, NovTmin, DecAccum10, DecTmin, FebPrec, MarTmax) where coefficients were significantly different from 0 (Table 3). Both models showed that yields increased with October precipitation (CFS = 3.5 kg/ha per mm; PHS = 4.4 kg/ha per mm). The higher the excess precipitation

(summed daily rainfall > 10 mm) in November and December, the lower the yield in CFS and PHS. March Tmax, which coincides with the grain filling stage, had a significant negative effect on both CFS (98.8 kg/ha decrease per 1° increase) and PHS (109 kg/ha decrease per 1°).

The PHS and CFS models showed different responses to December and February variables. December Tmin had a much larger negative impact on CFS yield than on PHS (−242 kg/ha decrease per 1° increase compared to −83 kg/ha). February Tmax showed a significant positive relationship with CFS but not with PHS yield, which stands in sharp contrast to significant negative effect both models show in response to March Tmax. February precipitation showed a significant positive effect on CFS yields, but not on PHS. The amount of variance explained by the CFS and PHS model with adding each additional month of weather data was different (Fig. 2). While the coefficient of determination ( $R^2$ ) generally increased when an additional month of weather predictors was added to either model, the PHS model showed a flattening in the amount of variance explained between December and March, whereas the CFS model  $R^2$  increased linearly between October and March (Fig. 3). These differing patterns of changes in  $R^2$  indicate that farmers may put more weight on recent weather events than the true weights. The PHS result also suggests that, of the variables we examined, October–December weather conditions and soil texture account for nearly all of the explainable variance in district-level yields.

To further test the relative importance of March weather, given it is

Table 3

A summary of results from the General Model Panel regression of PHS, CFS and diff = CFS - PHS. “ $\beta$ ” columns have the estimated coefficients, and the “p-value” column is the range of the resulting p-value from a student *t*-test of each corresponding predictor variable, where NS means not significant, or greater than 0.1.

| Variable                       | PHS<br>$\beta$ | PHS<br>p-value | CFS<br>$\beta$ | CFS<br>p-value | diff<br>$\beta$ | diff<br>p-value |
|--------------------------------|----------------|----------------|----------------|----------------|-----------------|-----------------|
| lambda                         | 0.22           | < 0.01         | 0.26           | 9.34E-04       | 0.45            | 5.09E-08        |
| (Intercept)                    | 5125.11        | < 0.0001       | 3955.64        | 1.04E-06       | −939.44         | 0.07            |
| SoilTexture: clay-fine loamy   | −327.19        | < 0.05         | −477.69        | 3.20E-03       | −183.29         | 0.15            |
| SoilTexture: fine loamy-clay   | 116.88         | NS             | 105.49         | 0.24           | −32.72          | 0.63            |
| SoilTexture: coarse-fine loamy | 66.45          | NS             | −15.63         | 0.91           | −128.77         | 0.22            |
| SoilTexture: coarse loamy      | −56.71         | NS             | −244.74        | 0.38           | −23.13          | 0.92            |
| SoilTexture: sandy             | −238.12        | < 0.05         | −401.74        | 3.00E-03       | −167.89         | 0.07            |
| OctPrec                        | 4.40           | < 0.0001       | 3.48           | 4.86E-03       | −0.11           | 0.92            |
| NovAccum10                     | −0.67          | NS             | −1.12          | 0.38           | −1.10           | 0.13            |
| NovTmin                        | 68.02          | < 0.05         | 134.91         | 5.33E-04       | 33.25           | 0.38            |
| DecAccum10                     | −1.06          | < 0.01         | −1.06          | 0.08           | −0.03           | 0.95            |
| DecTmin                        | −83.52         | < 0.05         | −242.50        | 4.72E-05       | −95.86          | 0.06            |
| FebPrec                        | 0.11           | NS             | 1.61           | 9.38E-04       | 1.23            | 5.46E-03        |
| FebTmax                        | −5.30          | NS             | 86.46          | 0.01           | 95.39           | 1.75E-03        |
| MarTmax                        | −109.03        | < 0.0001       | −98.84         | 1.30E-03       | −16.95          | 0.50            |

partially unknown to farmers, and to more finely evaluate CFS-PHS differences in earlier months, we took the difference in CFS and PHS yields, and re-ran the regressions with October–March weather variables and the soil texture predictor. March weather variables were not significantly related to the differences in yield estimates between the CFS and PHS (Table 3). The only three significant weather variables were December T<sub>min</sub>, February T<sub>max</sub>, and February precipitation, the same variables that showed differences in their effects within the separate CFS and PHS models. If farmers predicted perfectly based on pre-survey weather conditions, it is unlikely that pre-March weather variables would be significantly related to the CFS-PHS difference, which quantifies farmers' forecast biases. In this case, February precipitation and temperature were the most significant variables explaining this bias, implying that weather conditions immediately preceding the forecast month contributed the most to farmers' biases. According to the model coefficients, farmers were more likely to either overestimate yield more or underestimate yield less when February daily maximum temperature or the February total precipitation were higher (Table 3). Overall, this model explained 11% of the variation in CFS-PHS difference.

### 3.3. Can an empirical model outperform farmers' forecasts?

The RMSE of the CFS surveyed yield compared to PHS surveyed yield by district and year was 780 kg/ha (56% of mean PHS yield) with a 95th percent confidence interval of 775–786 kg/ha. Compared to this farmer forecasted yield, a regression tree-based ensemble method had lower prediction error, even when fit with just October weather data and soil condition variables (Fig. 4). The three models showing lowest prediction errors within the testing set were those fit with weather data from October only (692 kg/ha), October through January (685 kg/ha), or October through February (676 kg/ha). Adding March weather data didn't improve the testing set prediction accuracy, but the RMSE dropped substantially when April–June weather variables were also included as predictors (Fig. 4). These results further highlight the importance of weather in the month prior to planting for yield forecasting, as well as weather conditions just before and during the reproductive stages. Using this approach, data on mid-season weather and soil properties provided more accurate (13.3% less RMSE) district-level yield forecasts than the survey-based CFS. The results also suggest that weather during the harvest months (April–June) have a substantial impact on final yield.

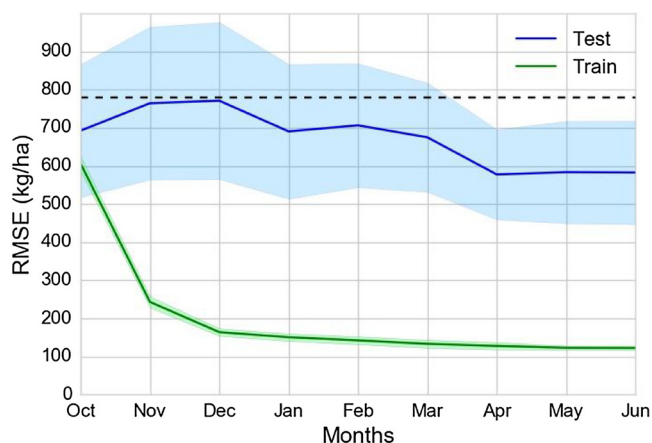


Fig. 4. Cross validation results of XGBoost predicted yield RMSE by threshold month. The blue line is the average of the testing set RMSE from a 10-fold cross validation, and the green line is the corresponding average of the training set RMSE. The shaded area represents the standard deviation of RMSE among the 10 folds of cross validation. The black dotted line is the average RMSE of CFS forecasted yield against PHS yield by district year.

## 4. Discussion

Our results hold several findings that are relevant to food security and related policies, which principally relate to the weather factors most influencing yield, the sources of difference between farmers' expectations of yield and actual yield, and the relative accuracy and timing of survey- versus model-based forecasts.

### 4.1. Primary weather factors influencing maize yield

The panel models revealed that early season precipitation and late season maximum temperatures were the dominant drivers of yield variation. Rainfall variables were most important in the early growing season, as low rainfall in October (prior to planting) and excessive rainfall in December (during planting) both negatively impacted yield. Dry conditions in February also reduced yields, but during this later stage of the growing season, temperature effects were much stronger, particularly the negative impacts of March maximum temperature, which was the most important weather variable impacting yield.

These findings regarding weather and yield reflect those of previous studies. Other research in Africa and elsewhere (Lobell et al., 2011; Schlenker and Lobell, 2010) has shown the important impact of maximum temperature on maize yield, especially during the reproductive period (typically February through March in Zambia). High temperatures during the reproductive period can lower yield by desiccating pollen (Lobell et al., 2013). More importantly temperatures above 30 °C can exacerbate crop water stress by increasing vapor pressure deficit (VPD), which in turn increases crop demand for soil water, in order to maintain photosynthetic rates, while simultaneously lowering water supply, by reducing transpiration efficiency (Lobell et al., 2013). Temperature impacts on yield are therefore closely related to soil moisture availability, thus a more direct measure of soil moisture and/or VPD could be more effective in predicting yield than temperature and precipitation measures.

Previous studies have also shown that excessive rainfall lowers yields, particularly during the planting period. The months with the highest rainfall are December and January for most of Zambia (Nicholson, 2000), which mainly overlap with the planting season and maize emergence. We found that the negative impact of excess rainfall during November and December had the most negative impacts on yield. This damage was either through flooding of newly planted maize or delayed through delay in planting, which was observed in Zimbabwe (Patt et al., 2005).

### 4.2. Factors influencing differences between farmers' expectations and actual yields

Given the insights provided by the PHS model into the factors influencing actual maize yields, we were able to use the CFS model to better understand sources of survey-based forecast errors. The difference between CFS and PHS yield is comprised of several sources of error and bias. These include measurement errors related to the total harvest amount reported by farmers, especially the planted or field area estimates reported by the farmers (used in both the CFS and PHS surveys), which can exhibit substantial bias (Carletto et al., 2015). Farmers' harvest forecasts may also be biased by an imperfect understanding of factors that influence yield, which include biophysical factors related to soil, weather, pests and diseases, as well as management practices.

An additional source of forecast error is the lack of knowledge farmers have regarding post-forecast weather conditions, which may damage standing crops still in the field, or cause losses during harvest or storage. Even though generalized weather forecasts are readily available via Zambian media (Weiss et al., 2000), it is unclear how accurate these are for different areas of the country, or how much farmers integrate them into their harvest expectations; previous work suggests that substantial interaction between forecasters and farming

communities is needed before farmers' adopt climate information (Rufino et al., 2013; Vogel and O'Brien, 2006). Farmers may actually evaluate weather within the context of crop performance, such that the crops' current health informs farmers' view of that season's weather conditions (Sutcliffe et al., 2016). Farmers' yield forecasts may therefore be based primarily on crop condition at the time of the CFS, and less on weather information available to the farmer, including post-survey weather forecasts. However, the relative contribution of these three sources of information (crop condition, prior weather, and weather forecasts) in shaping farmers' harvest expectations is unclear, and merits further research.

Furthermore, were farmers capable of perfect prediction, the amount of variation in CFS and PHS yields explained by soil and pre-forecast weather conditions would be the same, and the difference between CFS and PHS would be uncorrelated with those pre-forecast factors. Instead, we found that pre-forecast soil and weather factors explained about 13 percentage points less of the variation in CFS (49.6%) than PHS (62.3%). The CFS and PHS yield difference was most strongly correlated with the weather variables (February daily maximum temperature and precipitation) in the month preceding surveys, while the PHS model showed that weather variables between December and February added relatively little additional information about final yield (Fig. 2). We speculate that these differences reflect a proximity bias, in which farmers' predictions are most influenced by recent weather events, or their understanding of the yield impacts of recent events is more accurate, as memories of more distant events may be weaker (Patt and Schröter, 2008).

#### 4.3. Survey- versus model-based forecasts

The error of the CFS-derived yield forecast (RMSE = 780 kg/ha) yield was higher than the average of predictions derived from the empirical regression tree-based model fit with the October–March weather and soil variables (Fig. 4). This result suggests that having accurate weather forecasts for the months prior to March would allow governments and policy makers to forecast yields with similar or higher accuracy than level as the current survey-based approach farmers' forecast survey. Although the uncertainty is larger, our average model prediction means suggests that higher accuracy forecasts can be achieved even before February, using weather and soil variables alone. Since hunger-relief efforts can require up to six months from approval to delivery of food humanitarian endeavors to relieve hunger, once approved, take over six months to deliver food assistance (Brown et al., 2007), approaches that provide earlier warning to policy-makers can allow food security measures to be implemented in a more-timely manner. Our results showed that having weather and soil data alone and an empirical model could reach similar if not higher yield prediction accuracy as a late season survey, such that there would be more time for humanitarian aids and government efforts to reach to those in need.

Another factor favoring the adoption of model-based forecasts is the potential divergence between patterns of climate change and farmers' perceptions of those changes (Sutcliffe et al., 2016; Simelton et al., 2013; Rao et al., 2011; Osbahr et al., 2011). For example, previous studies in the region show that despite little to no trend in rainy season length, farmers perceive a substantial decrease in season length (Sutcliffe et al., 2016; Simelton et al., 2013). Farmers' perceptions in turn impact their behavior (Adger et al., 2009). In Malawi and Zambia, such perceptions have led farmers to increasingly adopt early maturing maize cultivars (Sutcliffe et al., 2016; Waldman et al., 2017), which may not be the best adaptation choice (Sutcliffe et al., 2016). This disconnect between climate perceptions and climate realization suggests a potential decrease in farmers' understanding of crop-climate relationships, and thereby the accuracy of their harvest expectations.

#### 4.4. Caveats

There are several caveats related to the methods used in our study. For one, the CHIRPS rainfall data we used might overestimate the number of rainy days (Funk et al., 2015). In addition, the CHIRPS dataset is initially calculated at a 5-day time step, and then downscaled to daily level. The daily metric may therefore fail to adequately represent rainfall dynamics, particularly rainfall extremes.

These potential biases in our rainfall data, assuming uniform, would not confound our findings, since we were analyzing the relative rather than absolute yield impact of spatial and temporal weather variability. Nevertheless, our analyses might underestimate the impact of extreme rainfall on yield during certain months. In addition to potential biases in the precipitation data used, a district level analysis might obscure more local relationships between yield and precipitation, as rainfall has greater spatial variability than temperature. Since the spatial resolution of weather, soil and yield data were different, our analysis had to aggregate all datasets to the district level. This lead to losses in spatial variation represented. Similarly, temporal aggregation inevitably smooths potential extreme events. The spatial and temporal aggregation in this study might also have diminished the significance of short-term or very localized events on yield—e.g. multi-day extremes (or sub-monthly time scale events). Future studies would need to apply more comprehensive datasets with harmonized resolutions as they become available, in order to ameliorate any issues caused by spatial or temporal mismatches.

Another potential limitation is that our methods might be prone to confounding caused by changing farmer practices, which have in turn altered the crop-climate relationship. For instance, Zambian farmers have increasingly adopted hybrid and early-maturing cultivars during the past 5–10 years, in response to policy incentives and perceived climate change (Smale and Jayne, 2003). In as much as the use of new, early maturing varieties increase drought tolerance, our coefficients may slightly overestimate the climate sensitivity of Zambian maize crops, particularly in relation to early season rainfall.

Lastly, the accuracy of our machine learning method relies on the comprehensiveness of scenarios represented in the model. This means that if there were some extreme weather events that were significantly beyond the conditions already considered in our model, prediction accuracy would decrease. A potential improvement on our approach could be to adopt yield estimation methods that combine remotely sensed vegetation indices with process-based crop models (e.g. Lobell et al., 2015). The advantage of such methods is that they are not conditioned on past crop-climate relationships, and therefore less prone to prediction errors under out-of-sample conditions, but they have much greater input data and calibration requirements.

#### 4.5. Broader implications

Our results have relevance for efforts to improve food security in the sub-Saharan Africa, which is under growing threat due to increasing climate uncertainty (Wheeler and von Braun, 2013). We found that early season (Oct–Dec) weather and soil conditions explained 60% of yield variation, and that a simple empirical model based on these variables can produce earlier and more accurate yield predictions than a survey-based forecast. Although forecast surveys such as the CFS provide information beyond expected harvests, our findings suggest that policy-makers could reduce costs and increase lead times by replacing the forecast component of the CFS with model-based approaches. Such models can be developed using freely available gridded weather and soil data, and further remote sensing methods could potentially replace important crop data that the surveys currently provide, such as planted area estimates (e.g. Boryan et al., 2011; Mathur and Foody, 2008). The use of such model-based approaches may also guard against potential declines in the skill of survey-based forecasts, caused by climate change undermining farmers' understanding of crop-climate

responses.

Our approach for comparing, and potentially improving upon, survey-based forecasts with relatively easy to implement empirical models can be applied to other countries and regions.

## Appendix A

## Acknowledgement

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**Table A1**  
Summary Statistics of numeric variables, with mean and standard deviation (sd).

| Variable Name      | Mean (sd)       |
|--------------------|-----------------|
| CFS (n = 420)      | 1395.6 (1033.2) |
| PHS (n = 490)      | 1365.4 (889.4)  |
| Diffy<br>(n = 420) | 61.6 (543.0)    |
| SoilpH             | 5.7 (0.32)      |
| OctPrec            | 21.9 (15.3)     |
| NovPrec            | 106.0 (44.52)   |
| DecPrec            | 220.0 (69.1)    |
| JanPrec            | 243.7 (72.5)    |
| FebPrec            | 195.7 (68.7)    |
| MarPrec            | 163.0 (71.3)    |
| OctDry             | 19.0 (5.60)     |
| NovDry             | 8.79 (3.80)     |
| DecDry             | 4.26 (4.07)     |
| JanDry             | 3.76 (2.24)     |
| FebDry             | 5.06 (3.75)     |
| MarDry             | 7.85 (4.07)     |
| OctAccum10         | 7.3 (8.69)      |
| NovAccum10         | 59.1 (33.5)     |
| DecAccum10         | 152.4 (72.1)    |
| JanAccum10         | 176.49 (79.4)   |
| FebAccum10         | 142.3 (66.5)    |
| MarAccum10         | 115.4 (64.4)    |
| OctTemp            | 26.2 (2.17)     |
| NovTemp            | 25.2 (1.90)     |
| DecTemp            | 24.1 (1.85)     |
| JanTemp            | 23.5 (2.01)     |
| FebTemp            | 23.8 (2.10)     |
| MarTemp            | 23.9 (2.07)     |
| OctTmax            | 33.6 (2.18)     |
| NovTmax            | 31.6 (1.90)     |
| DecTmax            | 29.5 (1.88)     |
| JanTmax            | 28.6 (2.26)     |
| FebTmax            | 29.0 (2.34)     |
| MarTmax            | 29.1 (2.60)     |
| OctTmin            | 18.8 (2.15)     |
| NovTmin            | 18.8 (1.91)     |
| DecTmin            | 18.7 (1.80)     |
| JanTmin            | 18.5 (1.85)     |
| FebTmin            | 18.8 (1.90)     |
| MarTmin            | 18.6 (1.74)     |

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