2. Spatial Analysis for Optimization of Fertilizer Use

Charles S Wortmann[1] cwortmann2@unl.edu, Maribeth Milner[1] and Gebreyesus Brhane Tesfahunegn[2]

[1]*Department of Agronomy and Horticulture, University of Nebraska-Lincoln, Lincoln, NE 68583*

[2]*College of Agriculture, Aksum University-Shire Campus, P.O. Box 314, Shire, Ethiopia*

2.1 Background

Sub-Saharan Africa (SSA) has a land area of 24 million km^2 and experiences widely varying crop growing conditions (Figure 2.1; HarvestChoice 2010). For most of Africa the mean monthly temperature (relative to sea-level) exceeds 18°C (64.4°F) year round (i.e. tropical) although parts of the continent experience temperatures as cool as 5°C (41°F) for one or more months (i.e. subtropical). Cool temperatures at high elevations impact crop growth (i.e. cool highlands) as well as timely precipitation.

Growing period (in days) is that time interval when mean temperature is 5°C or more and total water exceeds half the local potential evapotranspiration (PET). The arid to humid moisture class range represents less than 70 to over 270 day growing periods, respectively.

More climatic distinctions are evident at larger (or fine) scales as seen in Nigeria's agro-ecological zone (AEZ) map (Figure 2.2). The Sahelian, Sudanian and Guinean savanna to forest transition (White 1983) occurs with increasing rainfall and distance from the Sahara Desert. Deforested areas are referred to as derived savanna. The mid- and high-altitude classes correspond to the cool-humid class in Figure 2.1.

2.2 Inference space concept

The best crop production practices in one area can potentially inform decisions made in similar and possibly distant areas. One can estimate the inference space where research results are potentially relevant from critical crop-limiting thresholds. Likewise, queries of research sites' critical threshold values can identify relevant information for a location where research has not been conducted. The accuracy of a site's inference space model depends upon the understanding of a crop's response to the range of local environmental conditions and the availability and accuracy of regional data sets used to characterize limitations (Aiken et al., 2001).

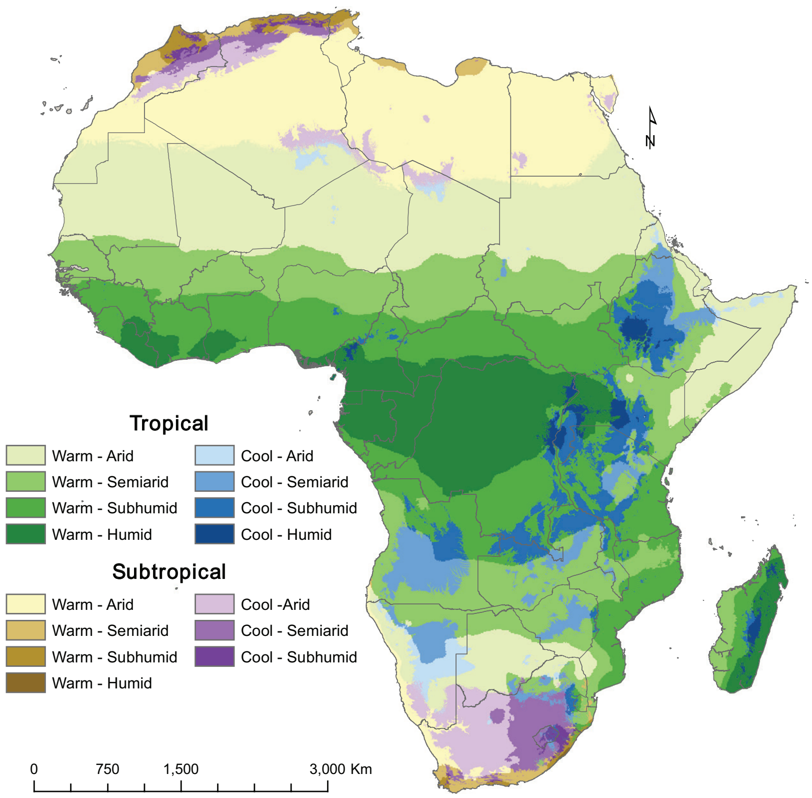

Figure 2.1. Africa climate zones from agro-ecological zones of sub-Saharan Africa (HarvestChoice 2010).

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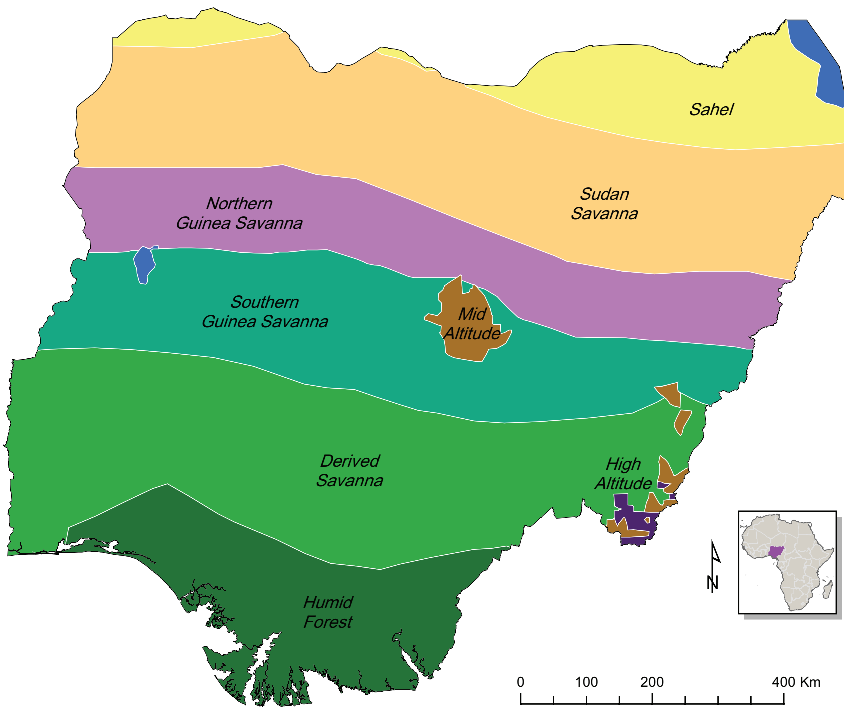

Figure 2.2. Nigerian climate zones.

2.3 Spatial data

Several agriculturally relevant SSA spatial data are available. Though the resolution is coarse, the data describes regional trends that influence potential crop production (Van Wart et al., 2013) and guide local crop suitability decisions. The Africa Soil Information Service (AfSIS) modelled soil properties at six soil depths. Several climate indices have been published (WorldClim, CGIAR CSI). The 2000 Shuttle Radar Topography Mission's elevation data are available worldwide for locations between 60°N and 56°S latitudes. Elevation derivatives are also available (HydroSHEDS) and the MAPSPAM project provides crop production estimates.

Spatial raster, vector and object data are processed with Geographic Information System (GIS) software programs. GIS packages often include complex spatial analysis and modelling tools in addition to basic mapping and data processing functionality. Several free (DIVA-GIS, GeoDa, GRASS, gvSIG Desktop and Mobile, SAGA, SPRING, QGIS, Whitebox Geospatial Analysis Toolbox) and proprietary (TerrSet (formerly IDRISI), ArcGIS, ERDAS IMAGINE) programs are available.

The Optimising Fertilizer Recommendations in Africa (OFRA) project strives to improve greatly the profitability of fertilizer use, especially for financially constrained fertilizer use as is the case for most smallholder farmers (Chapter 1). The OFRA approach uses results of past and recent research to determine crop nutrient response functions relevant for each site's agro-ecological zone (or inference space) so that economic analysis can be applied. Use of spatial data is important to finding and compiling information from research conducted under crop growing conditions similar to the conditions of the targeted recommendation domain.

2.4 OFRA Inference Tool

The OFRA Inference Tool (Wortmann and Milner 2015) is an ArcGIS 10.3 ArcPy script tool that identifies SSA research results and crop production estimates associated with growing conditions similar to those found at a user-defined point of interest (http://agronomy.unl.edu/OFRA).

The tool queries seven raster layers selected for agronomic importance. The amount of annual rainfall relative to potential evapotranspiration relates to water availability for crop production and is captured in CGIAR CSI's 30-arc second Global Aridity Index (Zomer et al., 2007, 2008). The manner in which temperature varies throughout a year impacts crop selection and is represented by WorldClim's 30-arc second Temperature Seasonality (bio4) layer (Hijmans et al., 2005). Mean temperature and the annual accumulation of growing degree days is dependent upon elevation, which is represented by Hydroshed's 3-arc second digital elevation model (DEM) (Lehner et al., 2008) resampled to 7.5 arc-seconds. Distance from the equator expressed as the absolute value of degrees latitude (as degrees x 1000; 7.5 arc-second) relates to rainfall distribution which changes from bimodal at the equator to increasingly unimodal with distance from the equator. Latitude also affects day length which impacts photoperiod sensitive crops. AfSIS 5-15 cm depth soil pH (as pHx10) (30-arc second; Hengl et al., 2014), sand content and soil organic carbon (SOC) content (7.5-arc second; Hengl et al., 2015) are included in the inference space analysis. Sand content is negatively related to clay content. Sand, pH and SOC are determinants of cation exchange capacity. Sand and SOC content are also important determinants of a soil's available water holding capacity. The average growing degree days (base 0) raster is highly correlated with elevation so it is not used to identify similarity but it is provided for reference. The raster was calculated from WorldClim.org's 30 arc-second mean monthly temperature data (Hijmans et al., 2005). All data are in geographic coordinates referenced to the WGS 1984 datum (GCS_WGS_1984).

The inference tool identifies the above seven raster values at the point of interest and uses a set of pre-defined queries to select crop nutrient response data from locations that have similar raster values. The query threshold values are editable from the script tool interface, but the query structure is not. The seven queries and editable default threshold values are:

Aridity Index (ai; range = 0 to 49,240):

If the selected ai value is <6000, then similarity equals the selected ai value + 1000. If ai is >6000, similarity equals ai values >5000.

Temperature Seasonality (ts; range = 62 to 8,933):

Temperature Seasonality similarity equals the selected ts value + 1000.

SOC (g/kg; 5-15 cm; range = 0 to 249):

If the selected SOC value is <35, then similarity equals the selected SOC value + 10. If soc is >35, similarity equals SOC values >25.

pH × 10 (range = 32 to 91)

If the selected pH × 10 value is <54, then similarity equals the selected pH × 10 value + 4. If pH × 10 is >54, similarity equals pH × 10 values >50.

Sand (%; range = 0 to 100):

If the selected sand value is >75, then similarity equals the selected sand value + 20. If sand is <75, similarity equals sand values <80.

Elevation (m; range = -178 to 5,844):

If the selected elevation value is <700, then similarity equals the selected elevation value + 1000. If elevation is >700, similarity equals elevation values >250.

Distance from Equator (DE; degrees × 1000; range = 0 to 11,691):

Distance from Equator similarity equals the selected DE value + 3000.

The tool queries two shapefiles, a point file of more than 5,300 georeferenced crop nutrient response functions and a polygon file of the 5-arc minute crop production raster cells with associated bean, cassava, cowpea, groundnut, maize, millet (pearl and small (finger)), Irish potato, rice, sorghum, soybean and wheat production (metric tons (mt)) values (HarvestChoice 2015a-l; You et al., 2014). The point file includes raster values at a representative point for each research plot (from which crop response is calculated) while the polygon file includes the median raster values associated with each 5-arc minute cell.

The OFRA Inference Tool outputs information for the point of interest's inference space: an Excel file containing a subset of crop response functions; two .pdf crop production maps (Figure 2.3); and a .dbf file containing crop production summaries (total production as metric tons and as the percentage of Africa's total crop production). The .dbf file also contains the point of interest's geographic coordinates and raster values as well as the queries used in the analysis.

The OFRA Inference Tool folder available at (http://agronomy.unl.edu/OFRA) includes

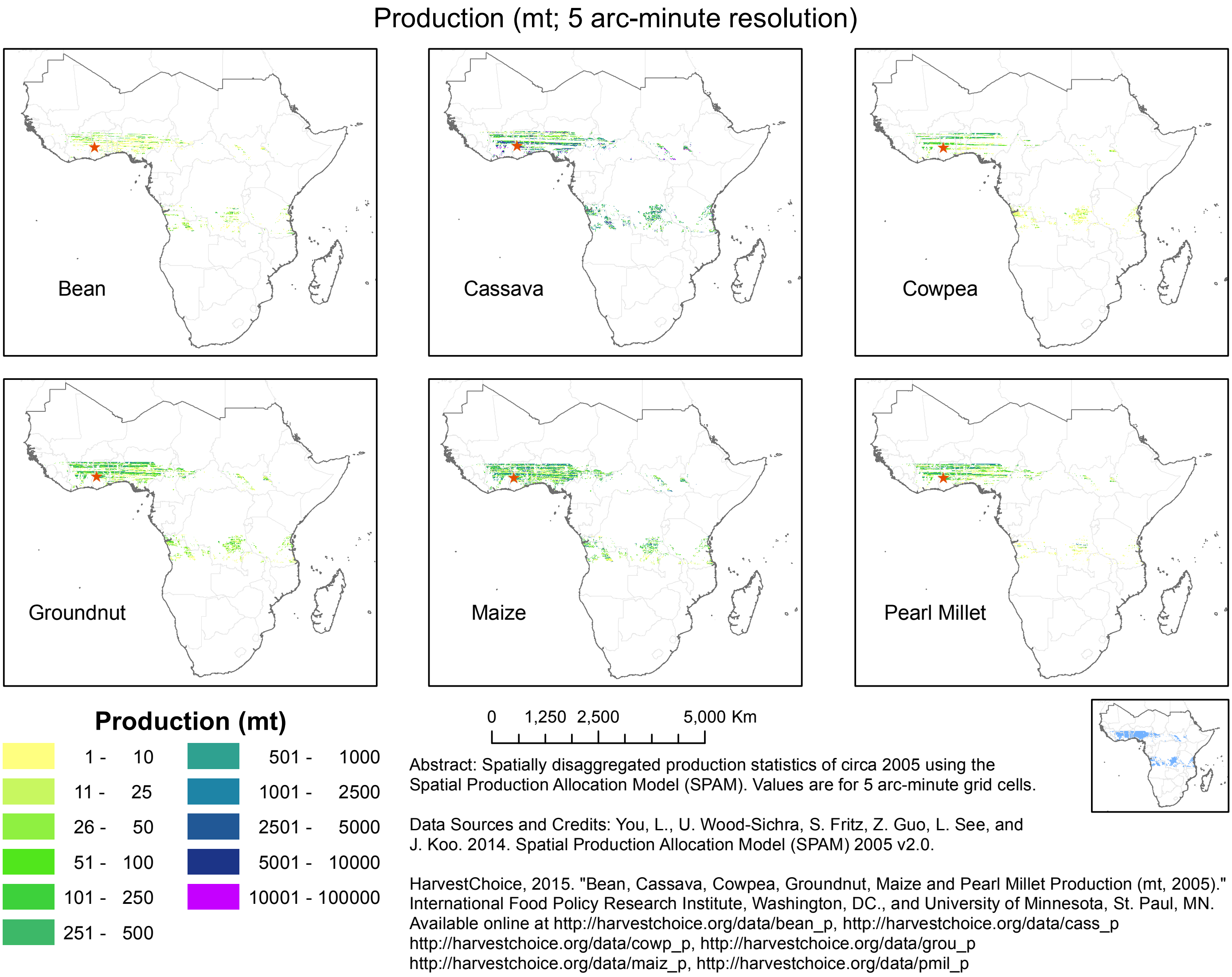

Figure 2.3. Bean, cassava, cowpea, groundnut, maize and pearl millet HarvestChoice production data associated with Wenchi, Ghana.

the ArcGIS script tool (OFRA Project.tbx), documentation, the GIS layers and data. The OFRA Inference Tool Documentation PowerPoint presentation provides instructions for use of the tool.

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