# Agricultural Land Suitability Assessment towards Promoting Community Crop Production in Tolon-Ghana

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## Abstract

Continuous use of agricultural land without periodic assessment of its suitability or performance for the cultivation of a specific crop could degrade soil fertility and compromise the long-term sustainability of the land to support production. Our aim is to use an integrated approach to assess agricultural land suitability in a small-scale farming system in the semi-arid region of northern Ghana, identify limiting factors for optimum crop production, and recommend intervention options towards sustainable farm management. We developed a data-driven model for land suitability analysis based on the Generalized Additive Models (GAM) approach. We validated the model with the actual yield data for six food crops (maize, pepper, yam, rice, peanut, and cowpea) under various biological, physical and chemical soil conditions across six communities. The result showed that the farmlands across the communities were highly suitable for maize and pepper but not suitable for cowpea. A qualitative validation method based on the contingency table showed the accuracy percentage of 84–100% for POD (Probability of Detection) and 6–21% for FAR (False alarm ratio) for all crops type. Hence, our model could be considered excellent to predict land suitability for different crop types. We recommend that stakeholders in the agricultural value chain should collaborate to develop low-cost and effective means of helping farmers determine the suitability of soils for specific crops to ensure that farmlands are not of depleted nutrients. In addition, periodic farmer training on appropriate farm management practices, including the right use of fertilizers, is needed.

## 1. Introduction

The continuous use of agricultural land without assessing its suitability or performance for the cultivated crop could lead to reduced productivity and further destruction of the land. In the semi-arid regions sub-Saharan Africa, continuous and unsustainable use of agricultural land has led to declines in soil organic carbon functions leading to severe reductions of 10–15% in crop yields (Nellemann et al., 2009). Factors such as anthropogenic disturbances from unsustainable resource utilization and poor management practices in the agroecosystem include intensive cultivation (Grace et al., 2006; Lahmar et al., 2012) overgrazing, and bushfires (Boakye-Danquah et al., 2014) account for the poor state of agroecosystems. Hence, assessing the suitability of existing agroecosystems to support different cropping regimes is critical to addressing food security in small-scale farming systems in the region.

Agriculture land suitability assessment entails the evaluation of the performance of a particular land under various types of crop production (Mu, 2006; Prakash, 2003). Land suitability assessment contributes to the sustainable management of the land and mitigates land degradation (Mazahreh, 1998), and promotes environmental stewardship. Land suitability is often determined by the appropriateness of the land for a specific use as well as the stakeholders' values and interests in a particular region (Bojorquez-Tapia et al., 1994) within a specific period. Suitability assessment can be done by considering several factors, including the physical environment, chemical, and socioeconomic data or indicators (Jafari and Zaredar, 2010). Generally, physical environmental elements are comparatively stable and predictable, but socioeconomic elements or factors tend to be complex since they are not easily controlled and thus tend to change more often, both spatially and temporarily (Zang et al., 2015). Under social and economic factors, land use decisions are influenced by the socioeconomic activities and the nature of the social organizations involved (Malczewski and Ogryczak, 1995). For instance, environmental conflicts can ensue when incompatible activities by different actors compete for available land (Bojorquez-Tapia et al., 1994). Also, changes in the cropping system due to increasing population growth, environmental degradation, and the need for higher yield or economic profits can lead to poor and unsustainable land use decisions (Zang et al., 2015). Unsustainable land use practices can affect the soil's chemical, biological, and physical condition with severe long-term consequences for land productivity.

Chemical properties of the soil such as electrical conductivity, nitrogen, soil moisture, organic carbon, organic matter, and pH determine the lands' suitability for producing different types of crops. Also, the biological, physical, and chemical conditions of organic carbon content can improve soil quality (Johnston et al., 2009) (Murphy, 2015), making it suitable for the productivity of various crops. Pan et al (2009) ascertained that variations in soil organic carbon result in variation in crop productivity and yield at different locations. Also, the pH of the soil impacts solubility and plant nutrients availability. The ability of soil to retain and distribute its nutrients is determined by the cation and anion exchange capacities. For instance, clayey soil or soil with a high organic matter has a higher cation exchange capacity (CEC), making it easier for soil nutrients to be absorbed by plants.

The discussions above suggest that effective land suitability analysis requires the combined and interactive evaluation of socioeconomic, physical, chemical, and bioclimatic factors (Dent and Young, 1981; Davidson, 2002). This makes land suitability assessment a daunting and complicated task (Keshavarsi et al., 2010). To address the complexity involved in land suitability analysis several methods, or approaches, such as Geographic Information System (GIS) and Remote Sensing (RS), and General Additive Models (GAMs), have been used. GIS and RS have been applied largely in land, soil, and crop suitability assessment (see (Bandyopadhyay et al., 2009; Mustafa et al., 2011). For instance, Bandyopadhyay et al., 2009 used GIS and RS data to develop an integrated land suitability potential (LSP) index for agricultural land potential by combining the texture of the soil, soil organic matter, depth, slope, and the land use. Most land suitability analyses often rely on multi-criteria analysis involving ranking, rating, and pairwise comparisons in the Analytic Hierarchy Process (AHP) (Chen and Khan, 2010; Benke and Pelizaro, 2010). These approaches depend mainly on a subjective decision based on expert preferences, experience, and personal judgment. To overcome these challenges, GAMs have also been employed severally in suitability analysis. GAM is a non-parametric statistic with a regression procedure that does not force data into linear relationships (Swartzaman et al., 1995). The advantages of GAMs include the ability to model interactions among variables to identify the threshold of each variable for habitat selection and quantify the potential abundance of an organism and the habitat model. GAMs have also been used to investigate trends in ecological data by mapping how target species relate to the environmental factors, in particular, to identify the habitat suitability for a wide range of species (see (Jowett and Davey, 2007; Mugo et al., 2010; Arrizabalaga et al., 2015; Setiawati et al., 2015)).

This study combined GAM and geospatial technologies to develop a land suitability model for six major food crops, namely maize, rice, yam, groundnut, pepper, and cowpea grown under small-scale subsistence farming systems in semi-arid communities of Northern Ghana. Using this approach, we aim to use an integrated approach to assess agricultural land suitability in a small-scale rainfed farming context. To do this, we first examine the cropping systems and existing farm management practices to identify limiting factors for optimum crop production and recommend intervention options for higher productivity. Next, we developed a crop suitability model based on crop requirements and soil characteristics that aim to utilize the land to achieve sustainability. Our analysis identifies the most suitable spatial pattern for particular food crops at the community level. GAM was applied to determine the soil and landscape features of specific food crops in the study area. This enabled us to reduce subjectivity by developing a data-driven model for land suitability analysis. This model was assessed by choosing the best available model, which includes a thorough data exploration and validation with actual yield data for six food crops (maize, pepper, yam, rice, groundnut, and cowpea) under various biological, physical, and chemical soil conditions.

## 2. Materials And Method

The research framework that guided this study is shown in Fig. 1. As already stated, the study aims to develop an integrated model that can assess agricultural land suitability for smallholder crop production systems. We integrated data from three primary sources and phases. The first phase involved assessing chemical and physical properties of the soil to determine the current state of the soil on croplands. The second phase involved assessing farm-management practices to understand the crop types and farm management decisions by farmers and derive yield data. The third phase involved estimating land use and land cover changes for the study site to create the current spatial pattern of the agricultural land uses; and extract soil moisture data from the study area. These three processes informed the design of the land suitability model. These

## 2.1 Study area

The study area is located in the Tolon District, in the Northern Region of Ghana; on latitude 9°15°N to 10°02°N; and longitude 0°53°W to 1°25°W. Six communities, Fihini, Cheshegu, Daboashie, Zagua, Kpalgun, and Yoggu, were selected as study sites within the Tolon district (see Fig. 2). Tolon district has a total population of 112,331 according to the 2010 census data (GSS, 2013) and a land size of 2,741km$^2$, with the density of the population estimated at around 40.9 per/km$^2$ (GSS, 2013). The area experiences irregular, intermittent, and often torrential rainfall (an annual average of 900mm to 1000mm). The rainy season often starts in April with the highest rainfall between July and September after which rainfall declines in October through to the long dry season from November to late March. In Tolon, the average temperature ranges from 25ºC to 36ºC, with the highest temperatures in March reaching up to 45ºC. The district also experiences a mean annual daily sunshine of 7.5 hours.

Tolon is typified by tropical grassland with sparse tree vegetation. The vegetation is dominated by the savannah woodland with perennial woody plants, grass, and dispersed dryness-tolerant trees such as neem trees, mango (Mangiferaindica), shea (Vitellaria paradoxa), baobab (Adanso-nia dipitata), kapok (Ceiba pentandra) and dawadawa (Parkiabiglobosa) (Antwi et al.,2014).

Agriculture is the mainstay of the economy in Tolon. Subsistence farming is the predominant livelihood activity in the district engaging more than 90% of the inhabitants. The primary food plants produced are maize, rice, sorghum, millet, cowpea, and yam (Boakye-Danquah, 2014). One of the major challenges to agricultural production in the Tolon District and northern Ghana is the decline in soil fertility (Songsore, 2011). A report by the Alliance for Green Revolution in Africa (AGRA) in 2011 estimated that 47% of the soils in study area are not suitable for producing crops, 28% are suitable, and 25% are marginal (AGRA, 2011). Soils are generally sandy loam and alluvial. The production of tuber and root crops thrives on Sandy loam soils (Baatuuwie et al., 2011). The degradation of land and loss of soil productivity because of vegetation cover loss and soil erosion are major concerns in the region (Songsore, 2011). Studies have shown that access to agricultural land is becoming scarce (Songsore, 2011), and fallow periods continue to decline (Boakye-Danquah et al., 2014), affecting the agricultural system's sustainability.

## 2.2. Data Acquisition Analysis

## 2.2.1 In situ Soil Properties

Within each community, soils were sampled from agricultural land according to the selected crop types. Horizon wise samples of soil were acquired from each profile and analyzed using standard analytical techniques for physical and chemical characteristics. For each representative plot, a tape measure measuring 100-m and a ranging pole was used to delineate a 12 m × 12 m square representative sub-plots. We gathered five (5) duplicate soil samples located at the ends of the delineated square plots and at the center, 30cm deep using an auger. We created a composite sample (Velasquez et al., 2007) by putting together the five (5) duplicate soil samples for each representative plot. All the samples were mixed in a bowl to form a unified sample for the particular land use sampled before being taken to the laboratory for investigation.

The analysis of the soil samples focused on the estimation of eight in situ soil, namely Electrical Conductivity (EC), Nitrogen (N), Organic Carbon (OC), Organic Matter (OM), pH, and particle size distribution (clay, sand, and silt). The electrical conductivity of the saturated soil mixture extract (ECE) was obtained using the Elico conductivity bridge (CM 82T) using the process given by (Jackson 1973). The Kjeldahl distillation method (Subbiah and Asija, 1956) was used to determine the nitrogen content. The OC and OM were assessed using the Walkley and Black moist oxidation technique (Jackson, 1973). Furthermore, the pH was measured in a 1:2 (soil: water) ratio (Page et al., 1982), and the soil particle size distribution was calculated by using the hydrometer method (Bouyoucos, 1926).

## 2.2.2 Agricultural land use mapping and on-Farm survey

Within each of the six communities, we worked with the farmers to delineate and map the community boundaries. Then, we marked the ground control point for the agricultural land-use (ALU) classification mapping process using GPS. We also conducted on-farm interviews with identified farmers or landowners to obtain historical information on agricultural land use types, the crop grown, farm size, yield of cultivated crops, and history and farm management practices between 2000 and 2015. Thus, we obtained from farmers the yield data for 2000, 2005, 2010, and 2015. We used a standardized survey questionnaire to interview the participants. The questionnaire consisted of open-ended and closed questions. In all, 132 on-farm interviews – Kpalgun (56), Daboashie (17), Cheshegu (14), Fihini (20), Zagua (25), Yoggu (115) were conducted. We complimented the on-farm data with information on farm management practices by drawing from previous studies conducted by the authors in the same communities (Boakye-Danquah et al., 2014; Antwi et al., 2018a, b).

In addition, extensive interviews were carried out with key informants in the community involving lead farmers, Chiefs, influential people, and an agricultural extension officer at the district level. The extensive interviews were held in August 2015. In addition, two researchers who have knowledge and experience through their work in the area were also interviewed to validate information and accounts by farmers regarding the agricultural land use practices and drivers of change in the community.

## 2.2.3 Acquisition and analysis of spatial data

Satellite images were used in this study to overcome the lack of soil properties in situ data and create the current spatial distribution of the ALU map. We collected Landsat images covering the study area in 2000, 2005, 2010, and 2015 during the dry season, with the cloud cover less than 1% and a spatial resolution of 30 m. The images between 2000 and 2015 were used to calculate soil moisture, while only the image for 2015 was utilized to map the agricultural land use of the study area. We also made use of the Shuttle Radar Topography Mission (SRTM) data to obtain a digital elevation model (DEM) having a spatial resolution of 30m for slope calculation. All the satellite data was downloaded from https://earthexplorer.usgs.gov/.

Using ENVI 4.2 software, the supervised classification system was performed on the images. The classification was done by using the maximum likelihood method with ground truth data obtained from fieldwork. Maximum Likelihood was chosen because it is still one of the most widely used supervised classification algorithms (Antwi et al., 2018b).

## 2.4 Land Suitability Model

The integrated land suitability modelling is shown in Fig. 3. Three main processes were involved in the modelling, namely, compiling database according to time and geographic properties, GAM assessment, and land suitability index assessment. Two main data types were fed into the model. These are soil chemical and physical properties and yield data. Ten variables of soil properties were applied in the model. All variables except soil moisture and slope were obtained by field survey. The soil data consisted of geographic locations and the magnitude of each soil property. To build spatial data distribution of the field survey soil properties, an interpolation process was used. We employed the Inverse Distance Weighted (IDW) interpolation technique.

The yield data sets included the location of farmlands (latitudes with their corresponding longitudes), the yield value of each food crop type (in kg), and the year. We focused on six major food crops, maize, pepper, yam, rice, groundnut, and cowpea, cultivated in the study area were chosen for analysis. The yield data for 2000, 2005, 2010, and 2015 were digitized and aggregated into the annual database and fed into the model.

## 2.4.1 Generalized Additive Models (GAM)

We applied the GAM to estimate the effects of soil properties of potential agricultural areas for each crop. This statistical method is mainly used for ecological modelling (Mugo et al., 2010; Setiawati et al., 2015; Zainuddin et al.,2008) species dynamic and habitat patterns. GAM has the advantage of allowing the analysis of non-parametric interactions and extending the utilization of additive models to data sets with non-Gaussian distributions.

GAM model was computed in *R version 3.03*, utilizing the *mgcv* package's gam feature (Wood, 2006), with the yield as a dependent variable and soil properties as explanatory variables. We adopted the following GAM model as shown in equation (Eq.) (2):

$$g = +f_1\left(X_1\right) + f_2\left(X_2\right) + \cdots + f_{10}\left(X_{10}\right) \tag{2}$$

In which g denotes the link function, μ is the estimated value of the explanatory variable (yield of each crop), α is the model constant, and f is a smoothing function of the Xi (soil properties) (Wood, 2006). X1 is clay, X2 is electrical conductivity, X3 is nitrogen, X4 is soil moisture, X5 is organic carbon, X6 is organic matter, X7 is pH, X8 is sand, X9 is silt, and X10 is the slope.

## 2.4.2 Crop and Land Suitability Index

The land suitability index is a quantitative measurement that assesses a given habitat's ability to sustain specific species (Oldham, 2000). We utilized the raster calculator feature in in ArcGIS 10.3 was used to calculate the land suitability index by combining the soil properties preference of each crop type based on GAM and accomplished by additive priority function P, as shown in Eq. (3) (Oldham, 2000; Store and Jokimaki, 2003) [42] .

$$P = (axX_1) + (bxX_2) + \cdots + (jxX_{10}) \tag{3}$$

In which P denotes the land suitability index, a,b,..j is the relative importance factor of Xi (i.e., weight factor). In this case, Xi corresponds to soil properties (i.e., clay, electrical conductivity, etc.)

$$X_i = \left\{ \begin{array}{c} 1, optimumvalueofsoilproperties \\ 0, nonoptimumvalueofsoilproperties \end{array} \right. \tag{4}$$

The optimum value of soil properties (i.e., clay, electrical conductivity, etc.) was calculated based on GAM results. In addition, the constant number of soil properties (i.e., a, b…j) was obtained by principal component analysis (PCA). Given a ten-variable data matrix, and 7889 samples of maize, 607 samples of pepper, 997 samples of yam, 1426 samples of rice, 3753 samples of groundnut, 735 samples of cowpea, the records first were centered on the means of each parameter using a covariance matrix (Eq.) (5). Next, the eigenvalues and corresponding eigenvectors were computed, as described in equations (6) and (7). Lastly, we determined the loading factor (i.e., (Eq.) (8)). Then, weight/ score in each variable can be calculated (i.e., (Eq.) (9)).

| | |
|---|---|
| $$A = \frac{1}{n}\sum(X-\mu)(X-\mu)^T$$ | **(5)** |
| $(A - \lambda I) = 0$ | (6) |
| $[A - \lambda][L] = [0]$ | (7) |
| $$Loading factor = Lx\sqrt{\lambda}$$ | (8) |
| $$Weight = loading factor x variance$$ | (9) |

The identifiers used in the preceding equations are described in this section. Where A, X, n, T, μ, λ, I, and L denote the covariance matrix, the explanatory variables, the sample number, the transposed function, the average of each explanatory variable, the eigenvalue, the identity matrix, and the corresponding eigenvector of X. The weight value was computed by multiplying the variance and corresponding loading factor for each variable by performing a PCA analysis. We utilized the *princomp* feature of R software version 3.03 to calculate the PCA analysis.

# 2.4.3 Model Validation

We conducted a validation process for this study based on the contingency table described in Table 1. In Table 1, the crop yield column "yes" was denotes as positive crop yield (i.e., crop yield higher than zero), and "no" was referred to as zero crop yield. The "A", "B", "C," and "D" in Table 1are the frequencies of the contingency table with no unit. "A" defines the frequency of correctly estimated positive crop yield. "B" represents when a positive crop yield is projected, but it does not occur. "C" means when positive crop yield is not estimated, but actual positive crop yield exists. "D" means correctly estimated zero crop yield.

Table 1
Contingency table for crop yield estimation

| In-situ data | | Potential area for crop | |
|---|---|---|---|
| | | Yes | No |
| Crop yield | Yes | A | C |
| | No | B | D |
| Note: A, B, C, D are the frequency (i.e., no unit) | | | |

To compute the percentage of accuracy, the Probability of Detection (POD), False Alarm Ratio (FAR), and Bias measurement were employed. POD describes how well the model projections detect the occurrence of positive crop yield, FAR denotes the proportion of diagnosed occurrences that turn out to be incorrect, while Bias indicates the closeness of the "yes" model and "yes" observation data. An ideal score of Bias is 1, less than 1 define under forecast, and higher than one (1) is over the forecast. This method is widely employed for evaluation assessment (Setiawati and Miura, 2016; Setiawati and Tanaka, 2017; Rimba et al., 2017). The POD, FAR, and Bias were computed by following equations (10), (11), and (12):

| |
|---|
| $$POD = \frac{A}{A+C} \quad (10)$$ |
| $$FAR = \frac{B}{A+B} \quad (11)$$ |
| $$Bias = \frac{A+B}{A+C} \quad (12)$$ |

## 2.4.4 Community validation and demonstration workshop

We also organized an intervention workshop to share the agricultural land suitability outcome with community participants. During the workshop, the project team printed hardcopies of the land suitability maps and made them available to community members. At the workshop, we demonstrated how to use the land suitability maps by using farm volunteers to identify their farm plots and crops suitable for cultivation. The workshop involved adult male and female farmers in each community. In Daboashie, Cheshegu, Fihini, and Zagua, approximately 60–70 farmers attended the demonstration workshop. Yoggu and Kpalgun had about 120–140 farmers participating in the demonstration workshop

# 3. Result And Discussions

## 3.1 Socio-demographic profile of farmers interviewed

Table 2 shows the socio-demographic characteristics of the farmers who participated in the on-farm survey. Across all the study communities, most of the farmers had no formal education. Although males dominated farming, we purposively sampled female farmers, as shown by the high level of female respondents across all study communities. Regarding the age of respondents, in Kpalgun and Daboashie communities, 62% of the total respondents were between ages 20 and 50, whereas the remaining 38% were aged above 50years. Also, in Fihini, 63% of the respondents were aged between 20 and 50years, while 37% were above 50years. Also, in Zagua, 72% of the respondents were aged between 20 and 50years, whereas 28% were above 50years. In Yoggu, 71% of the respondents were aged between 20 and 50years, while 29% were above 50years. Cheshegu, on the other hand, recorded the highest (86%) of respondents between 20 and 50 years, whereas the remaining 14% were specifically aged above 60years.

Table 2
Demographic Profile of Respondents

| Characteristics | Kpalgun | Daboashie | Cheshegu | Fihini | Zagua | Yoggu |
|---|---|---|---|---|---|---|
| Household Characteristics | | | | | | |
| No. Household | 111 | 32 | 26 | 38 | 48 | 216 |
| No. Sampled Farmers from unique households | 56 | 17 | 14 | 20 | 25 | 115 |
| Age of respondents | | | | | | |
| 20–50 years | 62 | 62 | 86 | 63 | 72 | 71 |
| Above 50 years | 38 | 38 | 14 | 37 | 28 | 29 |
| Gender of respondent | | | | | | |
| Male (%) | 53.6 | 47.1 | 57.1 | 50.0 | 48.0 | 47.8 |
| Female (%) | 46.4 | 52.9 | 42.9 | 50.0 | 52.0 | 52.2 |
| Education Level | | | | | | |
| Proportion Without Formal education (%) | 80.4 | 94.1 | 78.6 | 85.0 | 84.0 | 92.2 |
| Proportion with Formal education (%) | 19.6 | 5.9 | 21.4 | 15.0 | 16.0 | 7.8 |
| Primary Occupations | | | | | | |
| Farming (%) | 98 | 88 | 100 | 100 | 100 | 99 |
| Farming & Livestock (%) | 2 | 13 | - | - | - | 1 |
| Source: Author's field survey, 2015 | | | | | | |

## 3.2 Land use and land-cover distribution

We assessed the land use and land-cover distribution of the communities, focusing on agricultural land use (ALU) distribution and crop types. This was done in two main ways. First, we combined the satellite data and ground control points to understand the spatial distribution of ALU. Our findings showed nine (9) land use/landcover classes for the six (6) communities covering a total land size of over 2,440 ha (Fig. 4 and Table 3). Across the communities, Yoggu occupied the highest land area of around 800 ha, whereas Cheshegu (203 ha) had the lowest land area. Due to its large land area, Yoggu recorded the highest land use/landcover areas of all the nine classes of land use studied relative to the other communities. Of the 2,440 ha of land area, maize occupied the most extensive land coverage of about 16%, followed by the built-up/open land category (about 15%) and then yam and pepper farms occupying about 14% each. Waterbody was the lowest with less than a percentage coverage (Fig. 4 and Table 2).

In terms of relative coverages by percentages of the land use/landcover across the six communities, Dabogshei recorded the highest maize and pepper acreages of about 29% and 22%, respectively, while Zagua was observed to have recorded the lowest for these two crops with roughly 9% and 6% respectively (Table 3). On the contrary, Zagua has the largest land use/landcover areas for built-up/open land (29.4%) and rice cultivation (15.4%), whereas Dabogshei was seen to have the lowest coverages for both classes (Table 3). Land use activities for cowpea were highest in Dabogshei (13.1%) and lowest in Fihini (6.1%). Cheshegu recorded the most extensive area for groundnut with around 15% while being lowest for Yoggu and Fihini of about 8% each. Fihini had the largest yam (15.7%) land use while Dabogshei recorded the lowest with about 12%. Also, the fallow field's highest coverage was about 17% for Yoggu and around 4% least fallow area for Dabogshei. Effectively, this could mean that more lands in Yoggu were not in use during the assessment period compared to the other communities. Our analysis also showed that waterbodies were present only in Fihini (0.5%) and Yoggu (0.4%). In northern Ghana, water bodies are very important for household and on-farm activities, including support to dry-season farming.

Table 3
Area of Land Uses in the Study Communities 2015 (Unit: Ha; %)

| **Areas in ha** | | | | | | | |
|---|---|---|---|---|---|---|---|
| Landuse | Fihini | Dabogshei | Kpalgun | Yoggu | Cheshegu | Zagua | Total (Ha) |
| Maize | 77.31 (21.41) | 69.48 (28.56) | 66.87 (13.93) | 118.35 (14.49) | 37.17 (18.31) | 29.43 (8.83) | 398.61 |
| Fallow Field | 48.78 (13.51) | 10.53 (4.33) | 67.14 (13.45) | 138.33 (17.29) | 22.23 (10.95) | 22.05 (6.61) | 309.06 |
| Pepper | 51.57 (14.28) | 54.27 (22.31) | 55.8 (11.18) | 118.62 (14.82) | 30.78 (15.17) | 19.71 (5.91) | 330.75 |
| Rice | 45 (12.46) | 9.54 (3.92) | 32.76 (6.56) | 63.54 (7.94) | 22.32 (11.00) | 51.3 (15.38) | 224.46 |
| Groundnut | 30.33 (8.40) | 22.95 (9.43) | 56.7 (11.36) | 67.23 (8.40) | 29.7 (14.63) | 30.69 (9.20) | 237.6 |
| Cowpea | 22.05 (6.11) | 31.77 (13.06) | 58.23 (11.66) | 70.56 (8.82) | 18.72 (9.22) | 33.75 (10.12) | 235.08 |
| Waterbody | 1.89 (0.52) | 0.00 (0.00) | 0.00 (0.00) | 3.15 (0.39) | 0.00 (0.00) | 0.00 (0.00) | 5.04 |
| Built Up / Openland | 27.45 (7.60) | 16.2 (6.66) | 99.81 (19.99) | 106.83 (13.35) | 15.48 (7.63) | 98.1 (29.42) | 363.87 |
| Yam | 56.7 (15.70) | 28.53 (11.73) | 61.92 (12.40) | 113.67 (14.20) | 26.55 (13.08) | 48.42 (14.52) | 335.79 |
| Total | 361.08 (100.00) | 243.27 (100.00) | 499.23 (100.00) | 800.28 (100.00) | 202.95 (100.00) | 333.45 (100.00) | |

Crops cultivated in the communities have been reported in several studies (see Boakye-Danquah et L., 2014; Antwi et al., 2018 a, b). The most dominant crops cultivated in the communities are maize, rice, yam, groundnut, pepper, soya bean, cotton, millet, cowpea, tobacco, sorghum, and cassava. Among these, maize is the most dominant crop. In practice, most farmlands are intercropped with the major crops (e.g., maize, rice, yam) combined with minor crops (cowpea, tobacco, sorghum, and cassava). Cereal and legumes are the most rotated crops. Earlier studies have shown that in the Tolon area, crop rotation is a common soil conservation method because of its ease of integrating into the farming system (Okorley et al., 2002). Alternating legumes with cereals observed through the landscape monitoring at the community level is important for nitrogen fertilization in smallholder cultivation systems where organic amendments are low (Bationo et al., 2006).

Although crops traditionally grown in the communities have not changed for several decades, findings from a field survey showed that hybrid crop varieties, especially maize, peanuts, cowpea, and rice, are becoming common in the study communities. Agricultural marketing companies, research units, and extension officers from the main channels through which these crop varieties are introduced to the communities. Such new crop varieties have early maturity, more resistant against droughts and diseases, and yields are better (Quaye, 2008). However, challenges such as perceived better taste for local varieties, seasonal seed purchase, and higher use of fertilizer, insecticides, and pesticides for new crop varieties have affected the adoption of new crop varieties (FAO, 1997).

## 3.3 Farm management practices

Farm management is the process by which resources and situations are manipulated by the farm manager in trying, with less than full information, to achieve their goals (FAO, 1997) which is often that of maximum production returns. Earlier field work conducted by the authors (Antwi et al., 2018 a,b) observed farm management practices in the communities often involves two main activities: land preparation prior to cultivation and soil and land management. Land preparation typically begins after the harvest of the previous crop, that is if the land was cultivated in the previous year. Farmers normally begin by clearing and gathering remaining crop residues (if any) as well as cutting re-emerging shrubs and weeds, which are later burnt under control. Across the communities, controlled burning of weeds is a widespread practice for land preparation. Where farm residues that could not decompose from the previous harvest before the next farming season is burned. In such small-scale farming systems, burning is an inexpensive and time-saving way of controlling weeds, insects, diseases, and excess crop residue. However, burning can deprive the soil of its protective layer against erosion, reduces the amount of organic matter received through mulching, and destroys soil organisms that play vital roles in the formation of soil structure and composition (Ringius, 2002).

Besides burning, ploughing is also an important land preparation practice which allows soils to be easily worked within dry conditions where soil compaction is high (Farage et al., 2003). In the communities, most farmers rent mechanical loughs from wealthy farmers or use cow-powered ploughs, where possible. We also observed a widespread use of weedicides by some farmers as part of the land preparation process. The use of weedicides can increase the acidity or alkalinity of the soil and destroy micro-organisms if it is not applied properly. Moreover, for some farmers, land preparation can commence even a year before planting begins depending on the resources available to the farmer. On the field, we observed that some farmer had kept their cattle on their fallow land to feed and add manure to the land before land preparation begins the following season. However, most of the farmers we talked to indicated that fallow periods have consistently declined – the maximum number of years a farm can be allowed to fallow is two years. Similar observations on the reduction of fallow periods in northern Ghana have been reported in other studies (Boakye-Danquah et al.,2014; Songsore, 2011; Quaye, 2008).

After land preparation, farm management practices commonly adopted by farmers are diverse including composting, animal manure, chemical fertilizer, turning weeds under, mechanized ploughing, animal traction and crop rotation. Across the communities, the use of tractor ploughing was most widespread farm management practice, followed by chemical fertilizer application and crop rotation. Most farmers indicated they practice crop rotation to preserve and restore the fertility of the soils. Reza (2016) notes that crop rotation that efficiently combines a mix of nutrient-fixing crops and crops with different root structures improves the physical and chemical condition of soils leading to the overall improvement in the fertility of the soil (Reza, 2016). The use of organic fertilizers, namely animal manure was also a very common farm management practice although its use is limited due to its low availability, competing uses with other livelihood activities, and bulkiness in transporting to farms. It is important to emphasize that manure and chemical fertilizer (e.g., NPK 15 15 15, Ammonium sulphate, and urea) are mostly combined or alternated in most maize farms.

The application of chemical fertilizer to boost production is essential as soils in the northern savanna under continuous cropping, and inappropriate farm management practices have declined in fertility (Bationo et al., 2018). Although there are recommended amounts per acre or hector, our findings showed that farmers are often unable to use the recommended amounts of fertilizers or were often not applied due to financial constraints, unavailability of the product, and lack of access to government-subsidized fertilizers. Across the communities, farmers complained about the high cost of chemical fertilizer. In a related study (Arthur, 2014) found that availability and application of chemical fertilizers are dependants on factors such as basic price factors, risk aversion, and price control.

# 3.3 Crop and Land Suitability Determining Crop Suitability

Before assessing the land suitability index, the various relationship between the yield of each crop and soil properties was examined using the GAM approach. Table 4 lists the model variable and p-value.

Table 4
List predictor variables that gave significant value for each crop type

| Soil properties | Maize | Rice | Pepper | Yam | Groundnut | Cowpea |
|---|---|---|---|---|---|---|
| | p-value | p-value | p-value | p-value | p-value | p-value |
| s(Clay) | 0.0581 | 0.3633 | **0.0484*** | 0.6095 | **0.0000*** | 0.1614 |
| s(EC) | 0.0974 | 0.9940 | 0.4677 | 0.0550 | **0.0145*** | 0.4936 |
| s(N) | **0.0026*** | **0.0049*** | **0.0035*** | **0.0124*** | 0.1218 | **0.0003*** |
| s(NDWI) | 0.1156 | 0.2562 | 0.2933 | 0.2747 | **0.0000*** | 0.0087 |
| s(OC) | **0.0005*** | **0.0192*** | 0.8133 | **0.0423*** | 0.3961 | 0.8437 |
| s(OM) | **0.0005*** | **0.0072*** | **0.0410*** | 0.0720 | 0.1931 | **0.0000*** |
| s(PH) | 0.5408 | **0.0000*** | **0.0006*** | 0.0551 | 0.1283 | **0.0120*** |
| s(Sand) | **0.0025*** | **0.0042*** | **0.0007*** | 0.8187 | **0.0000*** | 0.4318 |
| s(Silt) | **0.0001*** | 0.1265 | 0.1031 | 0.0662 | **0.0010*** | 0.4332 |
| s(Slope) | 0.1123 | 0.5020 | 0.4364 | 0.4143 | 0.4007 | 0.8097 |

The predictor variables were significant when the P-value is less than 0.05. Based on Table 4, only some of the soil properties in the study area had a considerable impact on the yield of each food crop. For example, the soil properties that significantly impact maize were nitrogen, organic carbon, organic matter, sand, and silt. Therefore, we only used those predictor variables to estimate the optimum concentration and calculate the land suitability index. Combining the significant variable was considered the best GAM model for specific food crops; then, the optimum concentration can be evaluated. To avoid subjectivity while combining several layers of soil properties, the PCA approach was used. Table 5 shows the optimum concentration and weight in each soil property. Based on Tables 6 and 7, we can deduce that each crop type has its preference for soil properties. Thus, identifying the land suitability index for specific food crops was extremely important.

Table 5
Optimum concentration of significant soil properties and its weight.

| Crop type | Soil properties | Optimum concentration | Weight |
|---|---|---|---|
| Maize | s(N) | 0.01–0.2 | 0.23 |
| | s(OC) | > 0.54 | 0.28 |
| | s(OM) | < 0.85 | 0.28 |
| | s(Sand) | 45–65 | 0.25 |
| | s(Silt) | < 36 | 0.24 |
| Rice | s(N) | < 0.082 | 0.29 |
| | s(OC) | > 0.77 | 0.35 |
| | s(OM) | > 0.9 | 0.35 |
| | s(PH) | > 5.37 | 0.22 |
| | s(Sand) | > 58 | 0.31 |
| Pepper | s(Clay) | > 6.2.25 | 0.12 |
| | s(N) | 0.01–0.16 | 0.24 |
| | s(OM) | OM < 1.3 | 0.29 |
| | s(PH) | 5.5–6.8 | 0.14 |
| | s(Sand) | > 59 | 0.16 |
| Yam | s(N) | < 0.075 | 0.27 |
| | s(OC) | > 0.5 | 0.28 |
| Groundnut | s(Clay) | < 8 | 0.22 |
| | s(EC) | 45–300 | 0.19 |
| | s(NDWI) | 0.2–0.6 | 0.08 |
| | s(Sand) | < 63.5 | 0.21 |
| | s(Silt) | < 34 | 0.20 |
| Cowpea | s(N) | 0.052–0.08 | 0.24 |
| | s(NDWI) | < 0.39 | 0.06 |
| | s(OM) | 1-1.75 | 0.28 |
| | s(PH) | > 5.8 | 0.14 |

The land suitable index maps for the six communities are shown in Fig. 5–10. On the map green represents not suitable and red represents highly suitable for a particular food crop. In the Kpalgun community (Fig. 5), pepper was the most suitable commodity, followed by maize and rice. More than two-thirds of the community land. Particularly from the central portions to the north was highly suitable for pepper. However, cowpea and yam were the least suitable crop in Kpalgun.

In Fihini, maize and pepper were the most suitable crops covering over 90% of the landscape. Rice was highly suitable in the southernmost part of the community, where there are river valleys. However, most of the community land was least suitable for rice, groundnut, and cowpea.

The cultivated lands in Zagua were suitable for pepper, rice, and maize in descending order. The central portions of the landscape were moderately suitable for groundnut and yam. However, cowpea was the least suitable crop for Zagua.

In Cheshegu, the land was most suitable for rice, yam, and maize, but not for cowpea, while crops like maize, pepper, and groundnut thrived better on lands in Yoggu, but not rice, yam, and cowpea.

In Daboashie, the land was suitable for rice, pepper, yam, and maize but not for cowpea.

Based on previous research by (Avornyo et al., 2014), Fihini and Yoggu had the least number of households cultivating rice within the six communities in northern Ghana. This finding corresponds with the outcome of our model assessment, where agricultural lands in Fihinni and Yoggu were not suitable for rice. In general, all the study areas were not suitable for cowpea but highly suitable for maize and pepper. Thus, based on the ALU distribution in 2015 (Table 3), maize occupied most agricultural lands; this agrees with our land suitability index map.

# 3.4 Model Validation

Qualitative approach was used for model validation. We employed stratified random sampling to decide the sample size and data for each stratification. Out of 5013 samples, we randomly selected 485 samples point of rice, 2841 samples point of maize, 1055 samples point of groundnut, 164 samples point of yam, 274 samples point of pepper, and 194 sample points of cowpea (Table 6).

Table 6
Contingency table for rice, maize, groundnut, yam, pepper and cowpea

| Crop Type | In-situ data | Model | |
|---|---|---|---|
| | | Yes | No |
| Rice | Yes | 454 | 31 |
| N = 485 | No | 0 | 0 |
| Maize | Yes | 2444 | 176 |
| N = 2841 | No | 204 | 17 |
| Groundnut | Yes | 969 | 55 |
| N = 1055 | No | 20 | 11 |
| Yam | Yes | 150 | 3 |
| N = 164 | No | 11 | 0 |
| Pepper | Yes | 201 | 35 |
| N = 274 | No | 38 | 0 |
| Cowpea | Yes | 120 | 67 |
| N = 194 | No | 7 | 0 |

The data were stratified according to the proportion of crop type in the study area. We employed the quantitative method for validation which was based on the contingency table shown in Table 6. Based on Table 1, POD, FAR, and Bias was calculated, and the results are described in Table 7.

Table 7
Validation Result

| Crop Type | POD (%) | FAR (%) | BIAS |
|---|---|---|---|
| Rice | 100 | 6.4 | 1.07 |
| Maize | 93 | 7.7 | 0.99 |
| Groundnut | 98 | 3 | 1.04 |
| Yam | 93.17 | 20.26 | 0.95 |
| Pepper | 84.1 | 13.13 | 0.99 |
| Cowpea | 94.5 | 16.6 | 1.5 |

For example, the value of POD, FAR, Bias of Maize are 93%, 7.7%, and 0.99, respectively. It means 93% of the maize crop model areas were correctly identified, 7.7% of the model's predictions proved to be incorrect and the model has a very high similarity with the observation data. Overall, the POD, FAR, and Bias for rice, maize, groundnut, yam, pepper and cowpea type ranges were 84–100%, 6–21%, and 0.95-15, respectively. The above result implies that our model could be considered excellent for predicting land suitability for each crop.

## 3.5 Interventions towards Sustainable Land Utilization and Crop Production

Land suitability assessment is critical to optimizing crop yield and ensuring sustainable land management (Mazahreh, 1998). In the small-scale farming systems of northern Ghana, where soil fertility decline and land degradation are a significant challenge to food crop production (Songsore, 2011), suitability assessment of existing agricultural land use has become important. This study is the first to provide knowledge on crop-soil suitability to support adaptation to land degradation programs in northern Ghana.

By comparing the current cropping patterns with the soil and crop suitability model across six communities, our findings revealed that most farmers (in five of the six communities) across the landscape are cultivating the crops that are less suitable to the soil types identified in the communities; an outcome that necessitated the community validation and demonstration workshop. During the workshop, most farmers were surprised at the discrepancy between what the model showed and what they practiced on the farm. While some of the participants said they could consider the model in the farm decisions in the future when given more information, others thought a lot more goes into the decision (e.g., household food needs, market demands, cost of planting, etc.) on what to plant other than just the soil characteristics.

According to Sharifi, 2003, although agricultural decisions are evaluated based on social, environmental, and economic factors, economic viability often dominates these considerations. Thus, the trend observed in the study communities could also be due to economic and policy considerations that make cultivation of certain crops preferred even though available land suitability information may not support the crops grown. Cultivating crops on less suitable soils may lead to reduced yields and thus require more inputs for maximum returns. A study in East Africa with similar climatic characteristics as northern Ghana by (Fermont et al., 2010) showed that low soil fertility limited cassava response to N, P, or K fertilizers. Therefore, it is not surprising that most farmers now apply chemical fertilizer as a key farm management practice. The high use of chemical fertilizer is probable due to the low soil fertility and the quest for quick results. Government agricultural policies and programs should develop low-cost and effective means of helping farmers with information on the suitability of soils for specific crops to ensure that farmlands are not overwhelmed and that nutrients are not depleted in the long term (Sharifi, 2003).

It should be noted that soil structure and content are dynamic and change with environmental conditions and human activities changes. Thus, the soil structures in the study communities today may not have been the same 10 years ago and may not be the same 10 years to come. Therefore, information from land suitability analysis is not meant to restrict the crop selection choices of farmers but rather to provide them with needed information on what to do to ensure the soils are suitable for the crops they intend to cultivate. However, information from the crop suitability model can help to alter the level of organic matter or nitrogen in the soil or adjust the soil pH or electrical conductivity to suit specific crops. A study done by (Lal, 2006) showed that with every 1 Mg $ha^{-1}$ increase in soil organic carbon pool in the root zone, crop yields for wheat, rice, and maize increased significantly.

To resolve conflicts that may exist between increased farm productivity, income, and environmental concerns, systems and technologies that make maximum use of external inputs and natural resources and avoid degradation are put in place (Sharifi, 2003). This implies that, for one, the farmer must be provided with adequate training on up-to-date farm management practices that ensure that the right amount of fertilizers, be it organic or chemical, are applied on the farmlands, and the right choice of and combination of land preparation and management practices are observed. This is very much needed in the study communities as interviews with farmers revealed that some resorted to wrong farming practices due to financial and technological challenges and a lack of proper understanding and training. Future training sessions must focus on practices farmers can engage in to restore and keep deficient soil nutrients in the soil and how crop yields can be optimized.

# 4. Conclusion

This paper used an integrated approach to assess agricultural land suitability in semi-arid small-scale farming systems of northern Ghana. We developed a Generalized Additive Model (GAM) for land use and validated the model with the actual yield data for six food crops (maize, pepper, yam, rice, groundnut, and cowpea) under various biological, physical and chemical soil conditions. The model showed that most farmers across the landscape are not cultivating crops suitable to the soil types identified in the communities, thus limiting optimum crop production on available farmlands. Across the landscape, maize and pepper were generally the most suitable crops in all the study communities. However, analysis of cropping patterns through interviews with community members showed that maize, rice, yam, and peanut emerged as the top three crops cultivated. This discrepancy could be attributed to the unavailability of crop-soil suitability information needed to guide farmers in their crop choices. Government policies and programs that promote particular food and cash crops may need to consider the soil suitability of the communities to enable farmers to achieve optimum benefits. In addition, several farm managements practices such as inappropriate use of fertilizers, slash and burn method, and climate variability and change have negatively affected land productivity in the study communities. There is a need to support farmers with knowledge and information on land suitability under the current agroecosystem to guide farming decisions and effectively address the factors that negatively affect land productivity and sustainable land utilization.

# Declarations

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### 6. Author Declarations

### Authors' contributions

All authors contributed to the study's conception and design. Material preparation, data collection and analysis were performed by Effah Kwabena Antwi, Martiwi Diah Setiawati and Jacob Doku Tetteh. The first draft of the manuscript was written by all authors and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

### 6.2 Conflicts of interest/Competing interests

The authors declare that they have no known competing financial interests or personal relationships

that could have appeared to influence the work reported in this paper.


### 6.3 Funding (information that explains whether and by whom the research was supported)

No funding was received for this study."


### 6.4 Ethics Declaration statement

Not applicable

### 6.5 Consent to Participate

Not applicable

### 6.6 Consent for publication

Not applicable

### 6.7 Availability of data and material/ Data availability

The SRTM and LANDSAT satellite data can be accessed at the following link: https://earthexplorer.usgs.gov/

The field survey data is available by request to the corresponding authors.

## References


1. Alliance for Green Revolution in Africa (AGRA). (2011). Three Country (Burkina Faso, Ghana and Mali) Case Studies on the PASS Value Chain Strategy/Approach and its Effect on Smallholder Farmer Yields in Africa, Alliance for Green Revolution in Africa, Food and Nutrition Security Unit, University for Development Studies (FNSU-UDS), accessed June 19, 2020
2. Antwi, E. K., Boakye-Danquah, J., Asabere, S. B., Yiran, G. A., Loh, S. K., Awere, K. G., Abagale, F.X., Asubonteng, K.O., Attua, E.M., & Owusu, A. B. (2014). Land use and landscape structural changes in the ecoregions of Ghana. Journal of Disaster Research, 9(4), 452-467. doi: 10.20965/jdr.2014.p0452
3. Antwi, E. K., Boakye-Danquah, J., Gyekye, K. A., Barimah, A. O., Botchwey, I., & Ametepe, R. (2018). Examining farm management practices and implications for food crop production in semi-arid Ghana. In Saito, O., Kranjac-Berisavljevic, G., Takeuchi, K., A. Gyasi, E. (eds), Strategies for building resilience against climate and ecosystem changes in Sub-Saharan Africa (pp. 265-289). Springer, Singapore.
4. Antwi, E. K., Mensah, R., Attua, E. M., Yiran, G., Boakye-Danquah, J., Ametepe, R., & Boadi, D. A. (2018). Assessing land and ecosystem management at the local level in the savannah ecological zone and the implications for sustainability.

In Saito, O., Kranjac-Berisavljevic, G., Takeuchi, K., A. Gyasi, E. (eds), Strategies for Building Resilience against Climate and Ecosystem Changes in Sub-Saharan Africa (pp. 149-177). Springer, Singapore.

5. Arrizabalaga, H., Dufour, F., Kell, L.T., Merino, G., Ibaibarriaga, L., Chust, G., Irigoien, X., Santiago, J., Murua, H., Fraile, I., Chifflet, M., Goikoetxea, N., Sagarmínaga, Y., Aumont, O., Bopp, L., Herrera, M., Fromentin, J.M., & Bonhomeau, S. (2015). Global habitat preferences of commercially valuable tuna. Deep-sea Research Part II-topical Studies in Oceanography, 113, 102-112. https://doi.org/10.1016/j.dsr2.2014.07.001
6. Arthur, K. F., (2014). Effects of tillage and NPK 15-15-15 fertilizer application on maize performance and soil properties. (Master's thesis, Kwame Nkrumah University of Science and Technology Kumasi, Ghana).
7. Avornyo, V. K., Ito,O., Kranjac-Berissavljevic, G., Saito,S., Takeuchi, K.,(2014). Cropping system in some drought-prone communities of the Northern Region of Ghana: Factors affecting the introduction of rice. Journal of Disaster Research, 9 (4), 475-483. https://doi.org/10.20965/jdr.2014.p0475
8. Baatuuwie, B. N., Ochire-Boadu, K., Abdul-Ganiyu, S., & Asante, W. J. (2011). Assessment of soil and water conservation measures practiced by farmers: a case study in the Tolon-Kumbungu District of Northern Ghana. Journal of Soil Science and Environmental Management, 2(4), 103-109. https://doi.org/10.5897/JSSEM.9000009
9. Bandyopadhyay, S., Jaiswal, R. K., Hegde, V. S., & Jayaraman, V. (2009). Assessment of land suitability potentials for agriculture using a remote sensing and GIS based approach. International Journal of Remote Sensing, 30(4), 879-895. https://doi.org/10.1080/01431160802395235
10. Bationo, A., Hartemnink A., Lungo, O., Naimi, M., Okoth, P., Smalling, E., & Thiombiano, L. (2006). African soils: their productivity and profitability of fertilizer use. Agricultural systems, 94 (1), 13-25.
11. Bationo, A., Fening, J. O., & Kwaw, A. (2018). Assessment of soil fertility status and integrated soil fertility management in Ghana. In A. Bationo, D.Ngaradoum, S.Youl, F.Lompo, J.Fening (Eds.) Improving the Profitability, Sustainability and Efficiency of Nutrients through Site Specific Fertilizer Recommendations in West Africa Agro-Ecosystems (pp. 93-138). Springer, Cham. https://doi.org/10.1007/978-3-319-58789-9_7
12. Benke, K., & Pelizaro, C. (2010). A spatial-statistical approach to the visualisation of uncertainty in land suitability analysis. Journal of Spatial Science, 55, 257–272. doi: 10.1080/14498596.2010.521975
13. Boakye-Danquah, J., Antwi, E. K., Saito, O., Abekoe, M. K., & Takeuchi, K. (2014). Impact of farm management practices and agricultural land use on soil organic carbon storage potential in the savannah ecological zone of Northern Ghana. Journal of Disaster Research, 9(4), 484-500. doi: 10.20965/jdr.2014.p0484
14. Bojórquez-Tapia, L. A., Ongay-Delhumeau, E., & Ezcurra, E. (1994). Multivariate approach for suitability assessment and environmental conflict resolution. Journal of environmental management, 41(3), 187-198. https://doi.org/10.1006/jema.1994.1042
15. Bouyoucos, G. J. (1926). Estimation of the colloidal material in soils. Science, 64(1658), 362-362. DOI: 10.1126/science.64.1658.362
16. Chen, Y., Yu, J., & Khan, S. (2010). Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. Environmental Modelling & Software, 25(12), 1582–1591. doi: 10.1016/j.envsoft.2010.06.001
17. Davidson, D. A. (2002). The assessment of land resources: achievements and new challenges. Australian Geographical Studies, 40(2), 109-128. https://doi.org/10.1111/1467-8470.00167
18. Dent, D., & Young, A. (1981). Soil survey and land evaluation. George Allen & Unwin Publishers, London
19. FAO (1997). Farm Management for Asia: A Systems Approach. (FAO Farm Systems Management Series - 13) available at: Table of Contents (fao.org)
20. Farage, P., Pretty, J., & Ball, A. (2003). Biophysical aspects of carbon sequestration in drylands. University of Essex. Accessed on April 16, 2022, from https://www.fao.org/fileadmin/templates/nr/images/resources/pdf_documents/cseqbiophysicalaspectsdrylands.pdf

21. Fermont, A.M., Tittonel, P.A., Baguma,Y., Ntawuruhunga, P.,Giller,K.E. (2010). Towards understanding factors that govern fertilizer response in Cassava: lessons from East Africa. Nutrient Cycling in Agroecosystem, 86,133-151. https://doi.org/10.1007/s10705-009-9278-3
22. Ghana Statistical Service (GSS). (2013). 2010 Population & Housing Census: Demographic, Social, Economic & Housing Characteristics. Ghana Statistical Service.
23. Grace, J., Jose, S., Patrick, J. M., Heloisa, S., Miranda, & Ruben, M.A. (2006). Productivity and carbon fluxes of tropical Savannas. Journal of Biogeography, 33, 387–400. https://doi.org/10.1111/j.1365-2699.2005.01448.x
24. Jackson, M. L. (1973). Soil chemical analysis prentice hall of India. Pvt. Ltd. New Delhi, 498. jaipurbiofertilizers, 2018).
25. Jafari, S., & Zaredar, N. (2010). Land Suitability Analysis using Multi AttributeDecision Making Approach. International journal of environmental science and development, 1(5), 441. DOI: 10.7763/IJESD.2010.V1.85
26. Johnston, A.E., Poulton, P.R., Coleman, K. (2009). Soil organic matter: Its importance in sustainable agriculture and carbon dioxide fluxes. In D.L Sparks (Eds.), Advances in Agronomy, 101,1–57. https://doi.org/10.1016/S0065-2113(08)00801-8
27. Jowett, I. G., & Davey, A. J. H. (2007). A Comparison of Composite Habitat Suitability Indices and Generalized Additive Models of Invertebrate Abundance and Fish Presence–Habitat Availability. Transactions of the American Fisheries Society, 136(2), 428-444. DOI: 10.1577/T06-104.1
28. Keshavarzi, A., Sarmadian, F., Heidari, A., & Omid, M. (2010). Land suitability evaluation using fuzzy continuous classification (a case study: Ziaran region). Modern Applied Science, 4(7), 72-81. DOI:10.5539/mas.v4n7p72
29. Lahmar, R., Bationo, B. A., Lamso, N. D., Guero, Y., & Tittonell, P. (2012). Tailoring conservation agriculture technologies in West Africa semi-arid zones: building on traditional local practices for soil restoration. Field crops research, 132, 158-167. https://doi.org/10.1016/j.fcr.2011.09.013
30. Lal, R. (2006). Enhancing crop yields in the developing countries through restoration of the soil organic carbon pool in agricultural lands. Land degradation & development, 17(2), 197-209. https://doi.org/10.1002/ldr.696
31. Malczewski, J., & Ogryczak, W. (1995). The multiple criteria location problem: 1. A generalized network model and the set of efficient solutions. Environment and Planning A: Economy and Space, 27(12), 1931–1960. https://doi.org/10.1068/a271931
32. Mazahreh, S. (1998). Alternatives for Land Utilization in Arid to Semi-Arid Regions in Jordan. Unpublished Masters' Thesis, University of Jordan, Amman, Jordan.
33. Mu, Y. (2006). Developing a suitability index for residential land use: A case study in Dianchi Drainage Area (Master's thesis, University of Waterloo).
34. Mugo, R., Saitoh, S.-I., Nihira, A., & Kuroyama, T. (2010). Habitat characteristics of skipjack tuna (Katsuwonus pelamis) in the Western North Pacific. Fisheries Oceanography, 19, 382–396. https://doi.org/10.1111/j.1365-2419.2010.00552.x
35. Murphy, B.W. (2015). Impact of soil organic matter on soil properties-a review with emphasis on Australian soils. Soil Research, 53, 605–635. https://doi.org/10.1071/SR14246
36. Mustafa, A. A., Singh, M., Sahoo, R. N., Ahmed, N., Khanna, M., Sarangi, A., & Mishra, A.K. (2011). Land suitability analysis for different crops: a multi criteria decision making approach using remote sensing and GIS. Researcher, 3(12), 61-84.
37. Nellemann, C., MacDevette, M., Manders, T., Eickhout, B., Svihus, B., Prins, A., & Kaltenborn, B. (eds). (2009). The Environmental Food Crisis. The environment's role in averting future food crises. A UNEP rapid response assessment. United Nations Environment Programme, GRID-Arendal, UNDP, New York.
38. Okorley E. L., Mensah A. O., & Al-Hassan I. S. (2002). Transfer and adoption of soil and water conservation technologies in the Tolon-Kumbungu district of northern region of Ghana. Ghana Journal of Agriculture Science, 35, 189-195. DOI: 10.4314/gjas.v35i1.1860

39. Oldham, R. S., Keeble, J., Swan, M. J. S., & Jeffcote, M. (2000). Evaluating the suitability of habitat for the great crested newt (Triturus cristatus). Herpetological Journal, 10(4), 143-156.
40. Page, A. L., Miller, R. H., & Keeney, D. R. (1982). Methods of soil analysis. Part 2. Chemical and Microbiological Properties. 2nd. Am. Soc. Agron. Inc. Publisher Madison, Wisconsin, USA
41. Pan, G., Smith, P., Pan, W. (2009). The role of soil organic matter in maintaining the productivity and yield stability of cereals in China. Agriculture, Ecosystem & Environment, 129, 344–348. https://doi.org/10.1016/j.agee.2008.10.008
42. Prakash, T. N. (2003). Land suitability analysis for agricultural crops: a fuzzy multicriteria decision making approach. ITC.
43. Quaye, W., (2008). Food Security Situation in Northern Ghana, Coping Strategies and Related Constraints. African Journal of Agricultural Research. 3 (5), 334-342.
44. Reza, S. (2016). Crop Rotation-A Vital Component of Organic Farming. Permaculture Research Institute. Retrieved April 16, 2022, from https://www.permaculturenews.org/2016/06/15/crop-rotation-a-vital-component-of-organic-farming/#:~:text=Crop%20rotation%20helps%20improve%20soil,and%20healthy%20soil%20microbial%20community.
45. Rimba, A.B., Setiawati, M.D., Sambah, A.B., Miura, F. (2017). Physical Flood Vulnerability Mapping Applying Geospatial Techniques in Okazaki City, Aichi Prefecture, Japan. Urban Science, 1, 7. https://doi.org/10.3390/urbansci1010007
46. Ringius, R. (2002). Soil carbon sequestration and CDM: opportunities and challenges for Africa. Climate Change. 54, 471-495. https://doi.org/10.1023/A:1016108215242
47. Setiawati, M.D., Miura, F. 2016. Evaluation of GSMaP Daily Rainfall Satellite Data for Flood Monitoring: Case Study—Kyushu Japan. Journal of Geoscience and Environment Protection, 4, 101–117. DOI: 10.4236/gep.2016.412008
48. Setiawati, M.D., Sambah, A.B., Miura, F., Tanaka, T., & As-syakur, A.R. (2015). Characterization of bigeye tuna habitat in the Southern Waters off Java–Bali using remote sensing data. Advances in Space Research, 55, 732-746. https://doi.org/10.1016/j.asr.2014.10.007.
49. Setiawati, M.D., Tanaka, T. 2017. Utilization of Scatterplot Smoothers to Understand the Environmental Preference of Bigeye Tuna in the Southern Waters off Java-Bali: Satellite Remote Sensing Approach. Fishes, 2, 1-16. https://doi.org/10.3390/fishes2010002
50. Sharifi, M. A. (2003). Integrated planning and decision support systems for sustainable water resources management: concepts, potentials, and limitations. Seminar on Water Resources Management for Sustainable Agricultural Productivity, organized by Asian productivity organization, Lahore.
51. Songsore, J. (2011). Regional Development in Ghana: The Theory and Reality. Woeli Publishing Services, Accra
52. Store, R., & Jokimäki, J. (2003). A GIS-based multi-scale approach to habitat suitability modeling. Ecological Modelling, 169(1), 1-15. https://doi.org/10.1016/S0304-3800(03)00203-5
53. Subbiah, B. W., & Asija, G. L. (1956). A rapid procedure for the estimation of available micronutrient in soils. Current Science, 25, 259-260.
54. Swartzman G., Silverman E., & Williamson, N. (1995). Relating trends in walleye pollock (Theragra chalcogramma) abundance in the Bering Sea to environmental factors. Canadian Journal of Fisheries and Aquatic Sciences, 52, 369-380. https://doi.org/10.1139/f95-039
55. Velásquez, E., Lavelle, P., & Andrade, M. (2007). GISQ, a multifunctional indicator of soil quality. Soil Biology and Biochemistry, 39(12), 3066-3080. https://doi.org/10.5897/JSSEM.9000009
56. Wood, S. N. (2006). Generalized additive models: an introduction with R. Chapman and Hall/CRC.
57. Wu, B., Liu, N., & Zhao, H. (2006). PSMIX: an R package for population structure inference via maximum likelihood method. BMC bioinformatics, 7(1), 1-9. https://doi.org/10.1186/1471-2105-7-317
58. Zainuddin, M., Saitoh, K., & Saitoh, S. I. (2008). Albacore (Thunnus alalunga) fishing ground in relation to oceanographic conditions in the western North Pacific Ocean using remotely sensed satellite data. Fisheries

Oceanography, 17(2), 61-73. https://doi.org/10.1111/j.1365-2419.2008.00461.x

59. Zhang, J., Su, Y., Wu, J., & Liang, H. (2015). GIS based land suitability assessment for tobacco production using AHP and fuzzy set in Shandong province of China. Computers and Electronics in Agriculture, 114, 202-211. https://doi.org/10.1016/j.compag.2015.04.004

# Tables

**Table 1** Contingency table for crop yield estimation

| In-situ data | | Potential area for crop | |
|---|---|---|---|
| | | Yes | No |
| Crop yield | Yes | A | C |
| | No | B | D |

Note: A, B, C, D are the frequency (i.e., no unit)

**Table 2** Demographic Profile of Respondents

| Characteristics | Kpalgun | Daboashie | Cheshegu | Fihini | Zagua | Yoggu |
|---|---|---|---|---|---|---|
| **Household Characteristics** | | | | | | |
| No. Household | 111 | 32 | 26 | 38 | 48 | 216 |
| No. Sampled Farmers from unique households | 56 | 17 | 14 | 20 | 25 | 115 |
| **Age of respondents** | | | | | | |
| 20-50 years | 62 | 62 | 86 | 63 | 72 | 71 |
| Above 50 years | 38 | 38 | 14 | 37 | 28 | 29 |
| **Gender of respondent** | | | | | | |
| Male (%) | 53.6 | 47.1 | 57.1 | 50.0 | 48.0 | 47.8 |
| Female (%) | 46.4 | 52.9 | 42.9 | 50.0 | 52.0 | 52.2 |
| **Education Level** | | | | | | |
| Proportion Without Formal education (%) | 80.4 | 94.1 | 78.6 | 85.0 | 84.0 | 92.2 |
| Proportion with Formal education (%) | 19.6 | 5.9 | 21.4 | 15.0 | 16.0 | 7.8 |
| **Primary Occupations** | | | | | | |
| Farming (%) | 98 | 88 | 100 | 100 | 100 | 99 |
| Farming & Livestock (%) | 2 | 13 | - | - | - | 1 |

Source: Author’s field survey, 2015

**Table 3** Area of Land Uses in the Study Communities 2015 (Unit: Ha; %)

| **Areas in ha** | | | | | | | |
|---|---|---|---|---|---|---|---|
| Landuse | Fihini | Dabogshei | Kpalgun | Yoggu | Cheshegu | Zagua | Total (Ha) |
| Maize | 77.31 (21.41) | 69.48 (28.56) | 66.87 (13.93) | 118.35 (14.49) | 37.17 (18.31) | 29.43 (8.83) | 398.61 |
| Fallow Field | 48.78 (13.51) | 10.53 (4.33) | 67.14 (13.45) | 138.33 (17.29) | 22.23 (10.95) | 22.05 (6.61) | 309.06 |
| Pepper | 51.57 (14.28) | 54.27 (22.31) | 55.8 (11.18) | 118.62 (14.82) | 30.78 (15.17) | 19.71 (5.91) | 330.75 |
| Rice | 45 (12.46) | 9.54 (3.92) | 32.76 (6.56) | 63.54 (7.94) | 22.32 (11.00) | 51.3 (15.38) | 224.46 |
| Groundnut | 30.33 (8.40) | 22.95 (9.43) | 56.7 (11.36) | 67.23 (8.40) | 29.7 (14.63) | 30.69 (9.20) | 237.6 |
| Cowpea | 22.05 (6.11) | 31.77 (13.06) | 58.23 (11.66) | 70.56 (8.82) | 18.72 (9.22) | 33.75 (10.12) | 235.08 |
| Waterbody | 1.89 (0.52) | 0.00 (0.00) | 0.00 (0.00) | 3.15 (0.39) | 0.00 (0.00) | 0.00 (0.00) | 5.04 |
| Built Up / Openland | 27.45 (7.60) | 16.2 (6.66) | 99.81 (19.99) | 106.83 (13.35) | 15.48 (7.63) | 98.1 (29.42) | 363.87 |
| Yam | 56.7 (15.70) | 28.53 (11.73) | 61.92 (12.40) | 113.67 (14.20) | 26.55 (13.08) | 48.42 (14.52) | 335.79 |
| Total | 361.08 (100.00) | 243.27 (100.00) | 499.23 (100.00) | 800.28 (100.00) | 202.95 (100.00) | 333.45 (100.00) | |

**Table 4** List predictor variables that gave significant value for each crop type

| Soil properties | Maize | Rice | Pepper | Yam | Groundnut | Cowpea |
|---|---|---|---|---|---|---|
| | p-value | p-value | p-value | p-value | p-value | p-value |
| s(Clay) | 0.0581 | 0.3633 | **0.0484*** | 0.6095 | **0.0000*** | 0.1614 |
| s(EC) | 0.0974 | 0.9940 | 0.4677 | 0.0550 | **0.0145*** | 0.4936 |
| s(N) | **0.0026*** | **0.0049*** | **0.0035*** | **0.0124*** | 0.1218 | **0.0003*** |
| s(NDWI) | 0.1156 | 0.2562 | 0.2933 | 0.2747 | **0.0000*** | 0.0087 |
| s(OC) | **0.0005*** | **0.0192*** | 0.8133 | **0.0423*** | 0.3961 | 0.8437 |
| s(OM) | **0.0005*** | **0.0072*** | **0.0410*** | 0.0720 | 0.1931 | **0.0000*** |
| s(PH) | 0.5408 | **0.0000*** | **0.0006*** | 0.0551 | 0.1283 | **0.0120*** |
| s(Sand) | **0.0025*** | **0.0042*** | **0.0007*** | 0.8187 | **0.0000*** | 0.4318 |
| s(Silt) | **0.0001*** | 0.1265 | 0.1031 | 0.0662 | **0.0010*** | 0.4332 |
| s(Slope) | 0.1123 | 0.5020 | 0.4364 | 0.4143 | 0.4007 | 0.8097 |

**Table 5** Optimum concentration of significant soil properties and its weight.

| Crop type | Soil properties | Optimum concentration | Weight |
|---|---|---|---|
| Maize | s(N) | 0.01-0.2 | 0.23 |
| | s(OC) | > 0.54 | 0.28 |
| | s(OM) | < 0.85 | 0.28 |
| | s(Sand) | 45-65 | 0.25 |
| | s(Silt) | <36 | 0.24 |
| Rice | s(N) | <0.082 | 0.29 |
| | s(OC) | >0.77 | 0.35 |
| | s(OM) | >0.9 | 0.35 |
| | s(PH) | >5.37 | 0.22 |
| | s(Sand) | >58 | 0.31 |
| Pepper | s(Clay) | >6.2.25 | 0.12 |
| | s(N) | 0.01-0.16 | 0.24 |
| | s(OM) | OM<1.3 | 0.29 |
| | s(PH) | 5.5-6.8 | 0.14 |
| | s(Sand) | >59 | 0.16 |
| Yam | s(N) | <0.075 | 0.27 |
| | s(OC) | >0.5 | 0.28 |
| Groundnut | s(Clay) | <8 | 0.22 |
| | s(EC) | 45-300 | 0.19 |
| | s(NDWI) | 0.2-0.6 | 0.08 |
| | s(Sand) | <63.5 | 0.21 |
| | s(Silt) | <34 | 0.20 |
| Cowpea | s(N) | 0.052-0.08 | 0.24 |
| | s(NDWI) | <0.39 | 0.06 |
| | s(OM) | 1-1.75 | 0.28 |
| | s(PH) | >5.8 | 0.14 |

**Table 6** Contingency table for rice, maize, groundnut, yam, pepper and cowpea

| Crop Type | In-situ data | Model | |
|---|---|---|---|
| | | Yes | No |
| Rice | Yes | 454 | 31 |
| N = 485 | No | 0 | 0 |
| Maize | Yes | 2444 | 176 |
| N = 2841 | No | 204 | 17 |
| Groundnut | Yes | 969 | 55 |
| N = 1055 | No | 20 | 11 |
| Yam | Yes | 150 | 3 |
| N = 164 | No | 11 | 0 |
| Pepper | Yes | 201 | 35 |
| N=274 | No | 38 | 0 |
| Cowpea | Yes | 120 | 67 |
| N=194 | No | 7 | 0 |

**Table 7** Validation Result

| Crop Type | POD (%) | FAR (%) | BIAS |
|---|---|---|---|
| Rice | 100 | 6.4 | 1.07 |
| Maize | 93 | 7.7 | 0.99 |
| Groundnut | 98 | 3 | 1.04 |
| Yam | 93.17 | 20.26 | 0.95 |
| Pepper | 84.1 | 13.13 | 0.99 |
| Cowpea | 94.5 | 16.6 | 1.5 |

# Figures

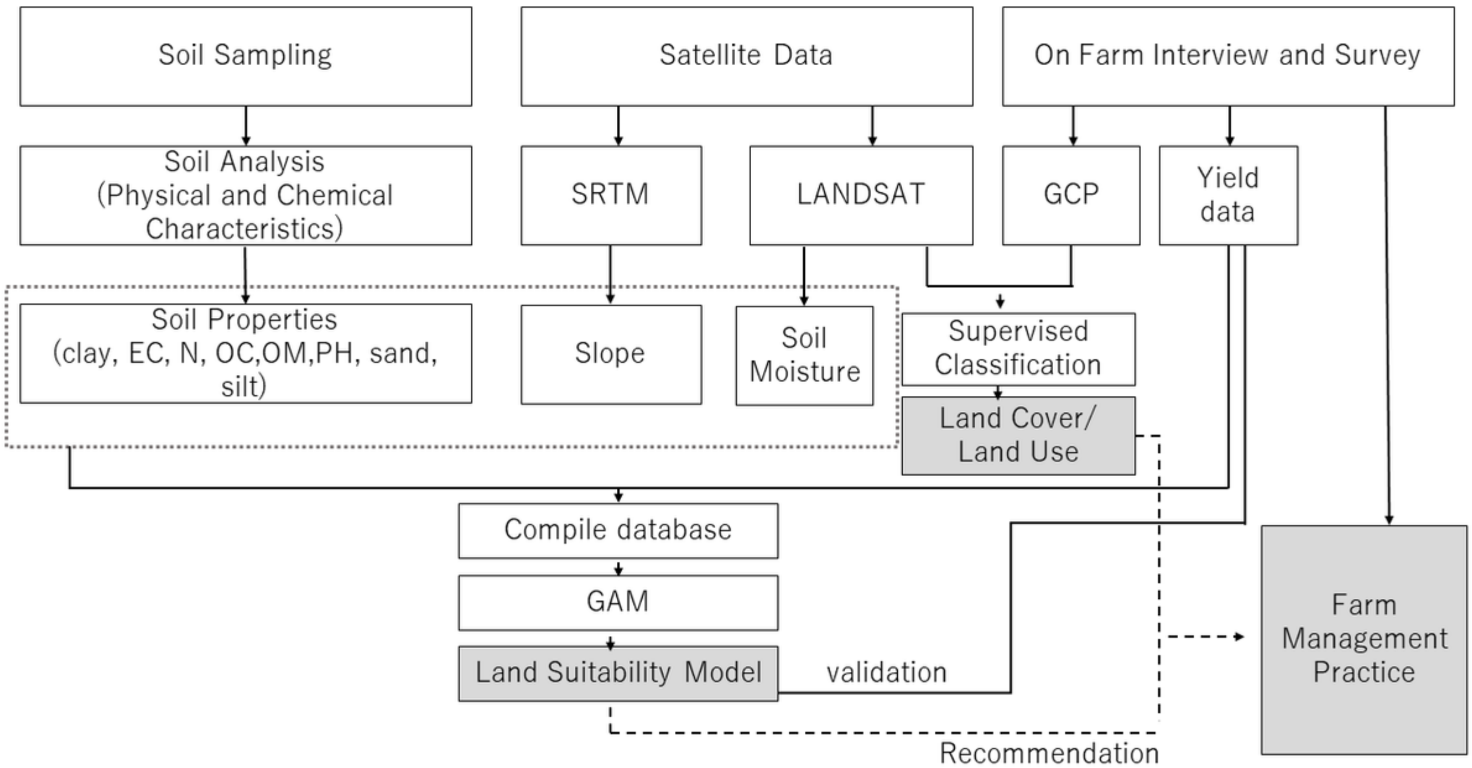
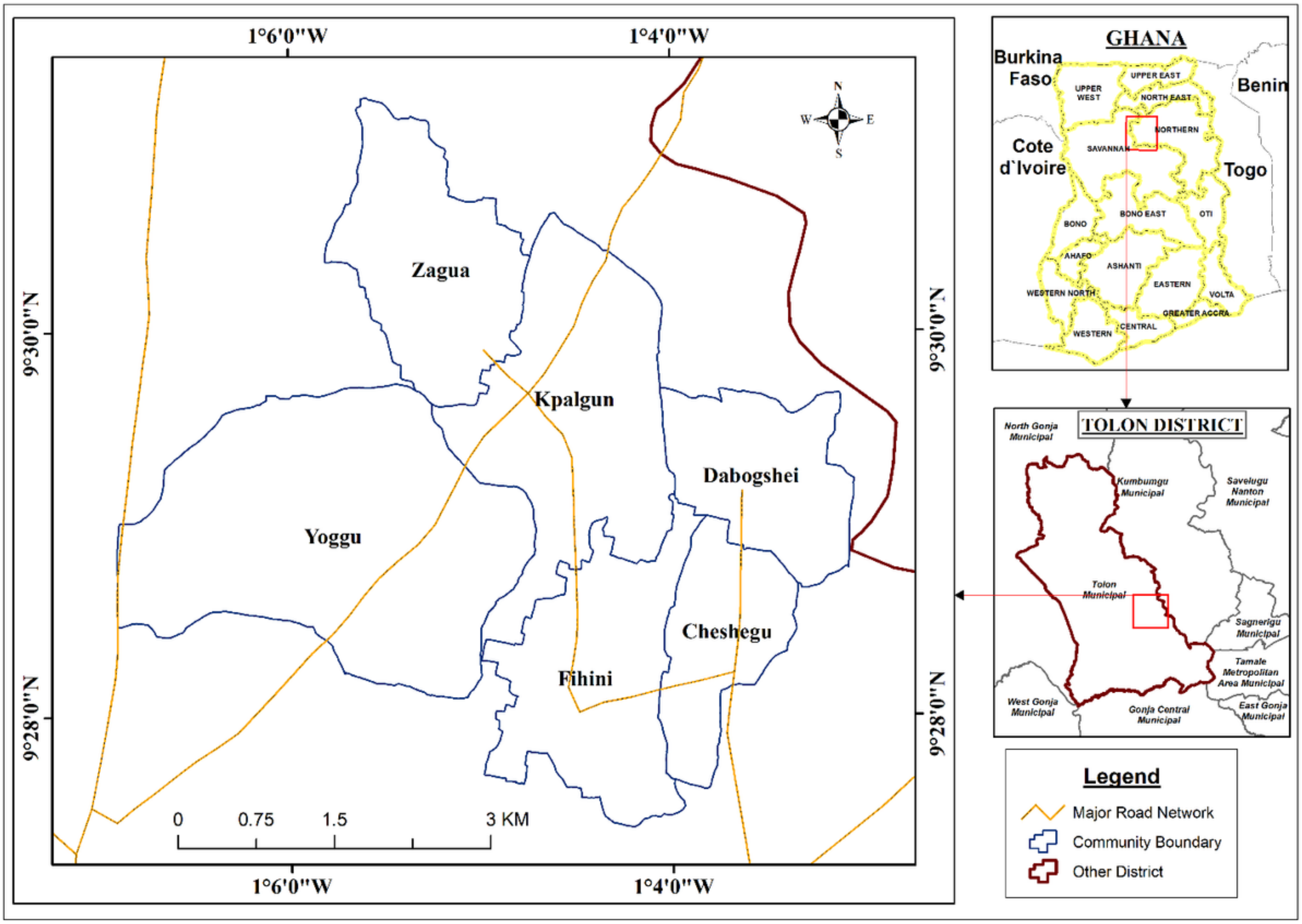



**Figure 1**

Research Framework




## Figure 2

Boundaries of the Study Communities in the Tolon District in the Northern Region of Ghana

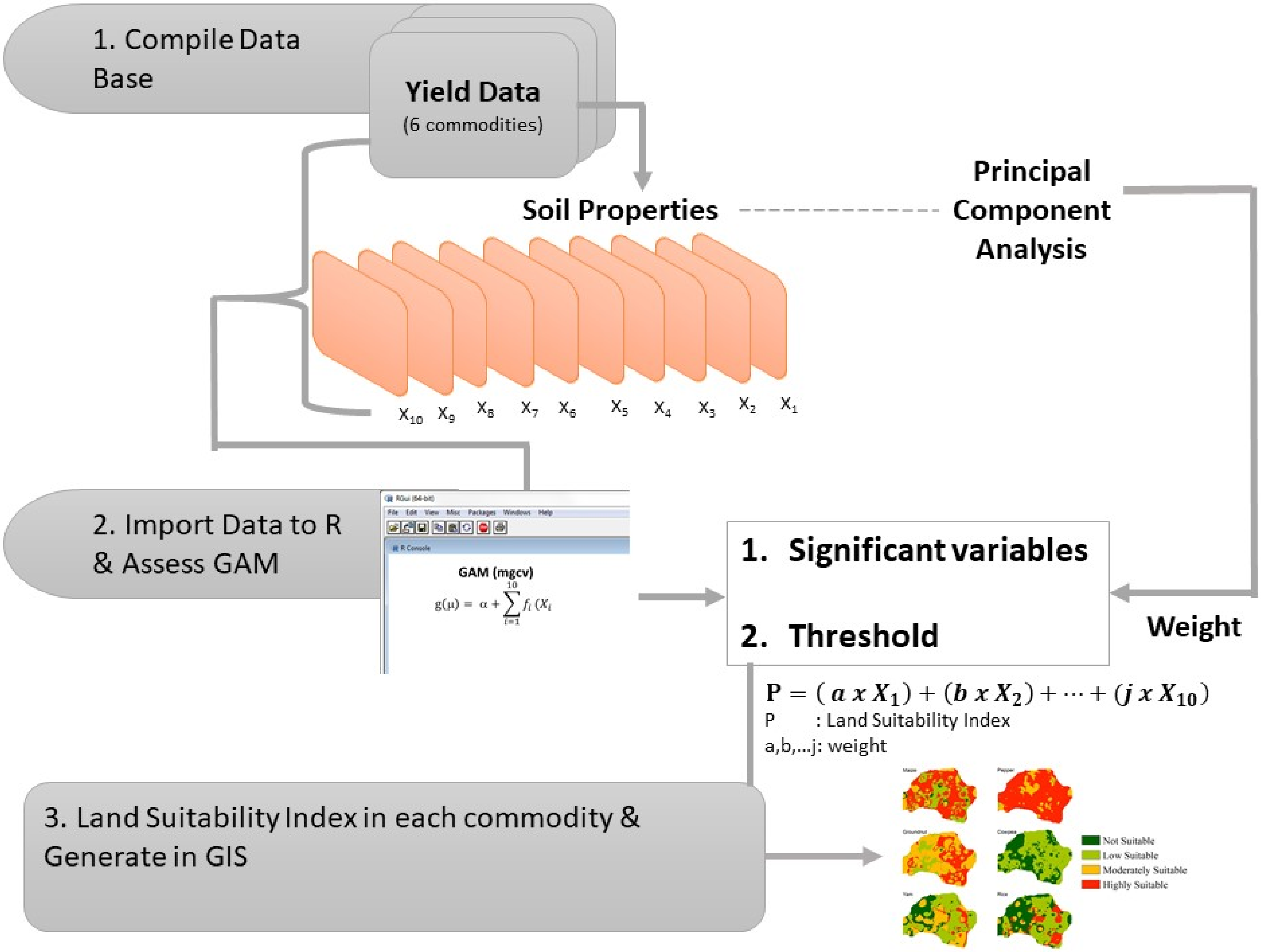



**Figure 3**

Land Suitability Modelling Flow chart

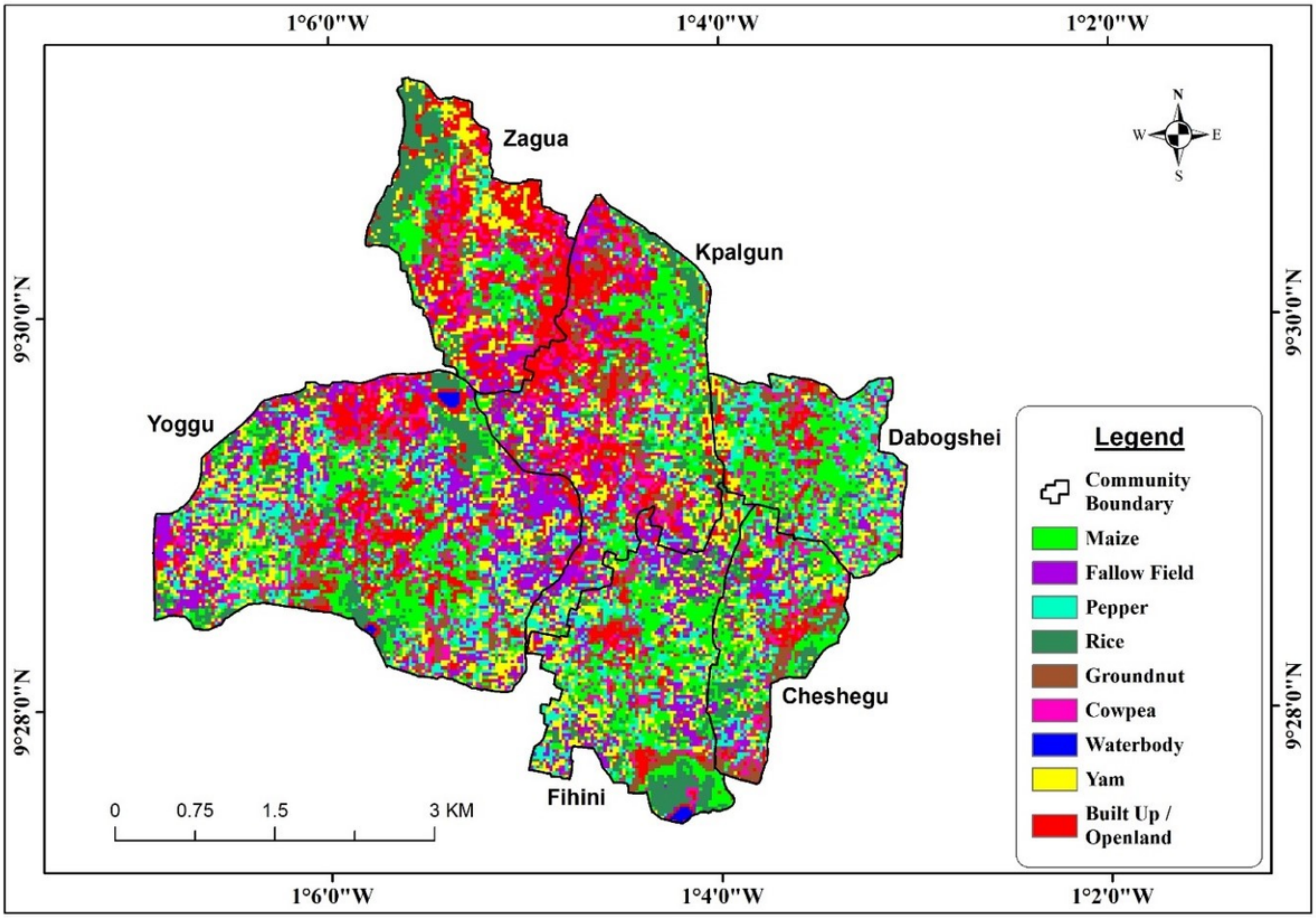
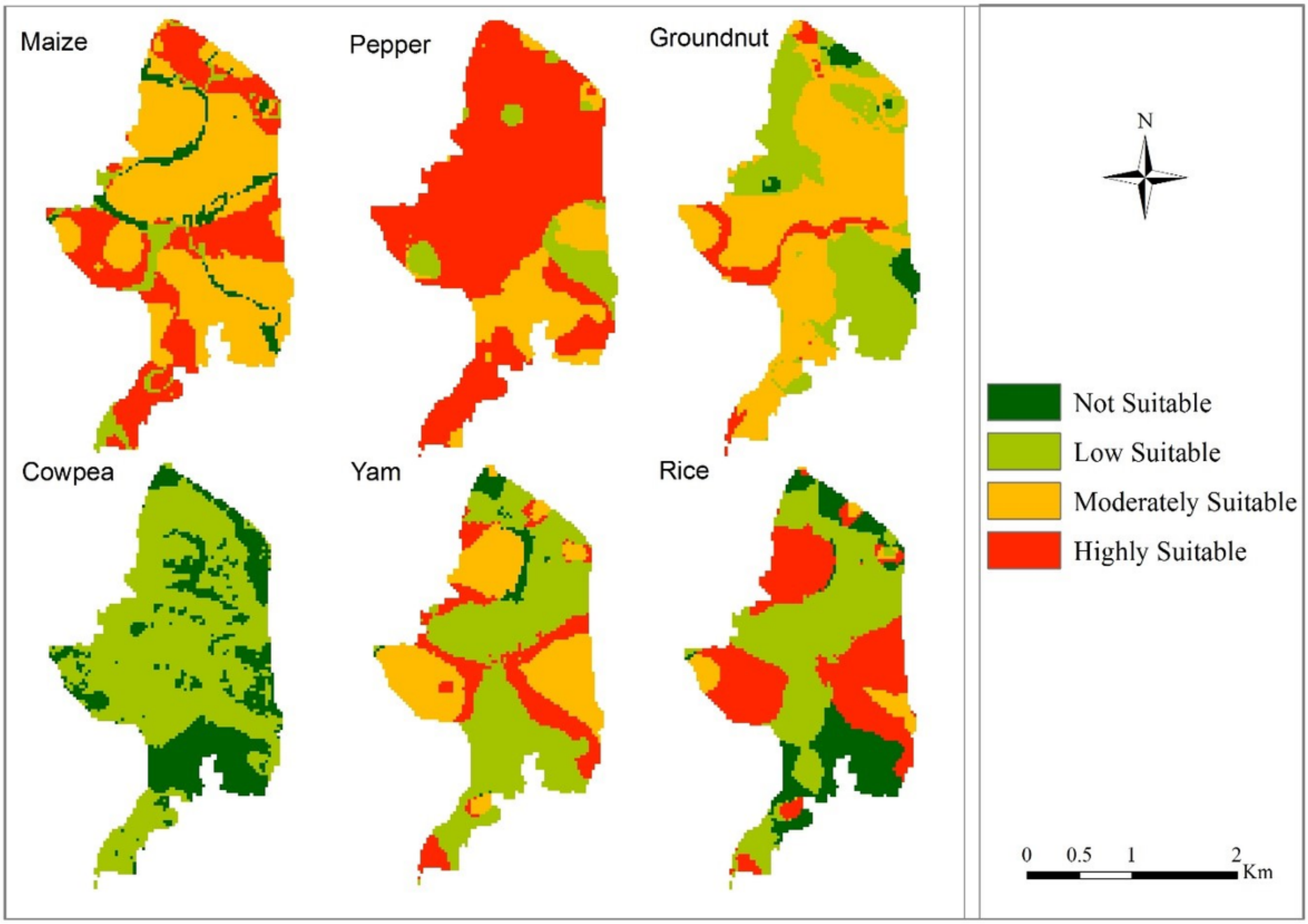



Figure 4

Agricultural Land Use and Other Land Uses in the Years 2015




## Figure 5

Agricultural Land Suitability Map for Crop Production in Kpalgun

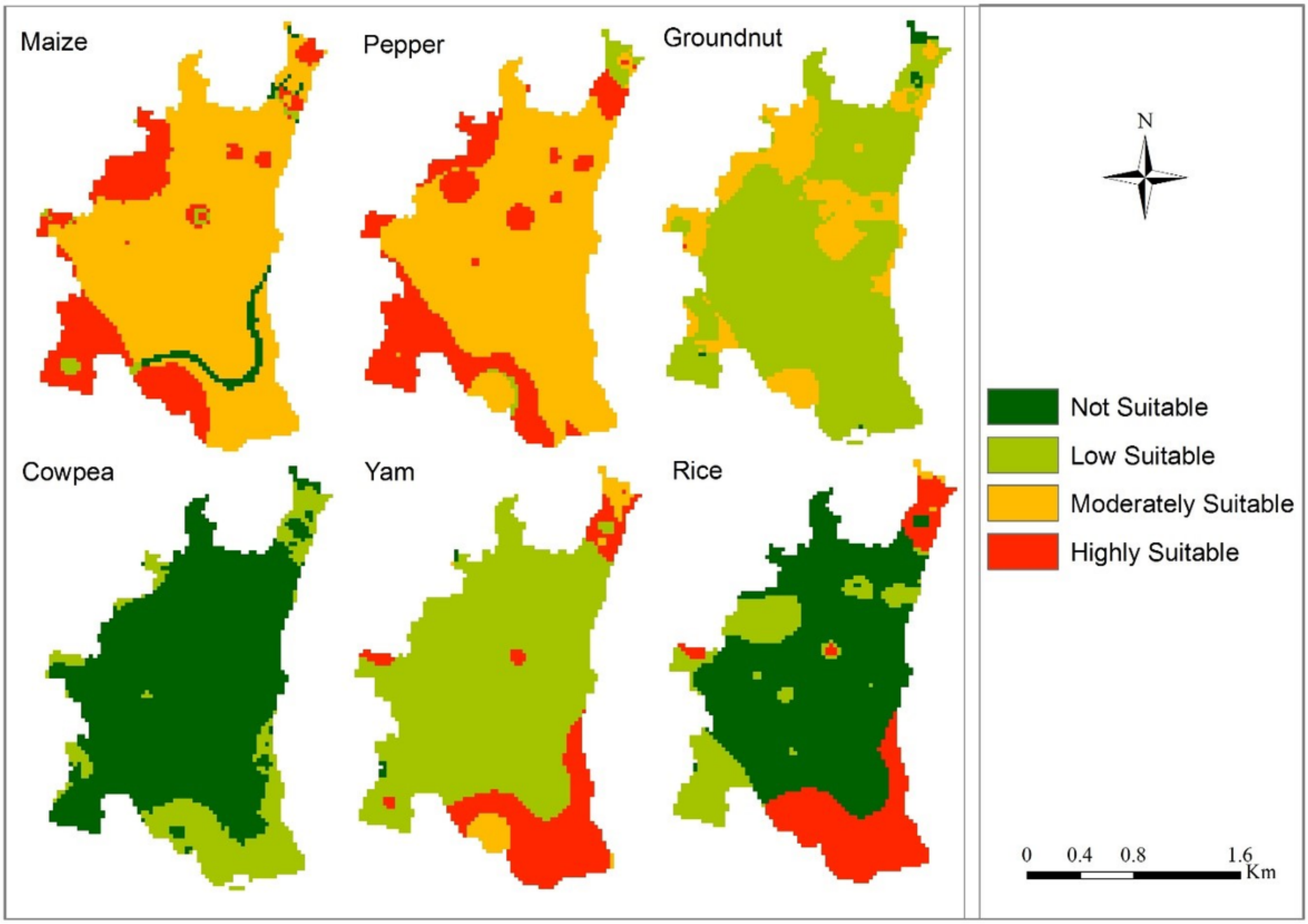



**Figure 6**

Agricultural Land Suitability Map for Crop Production in the Fihini

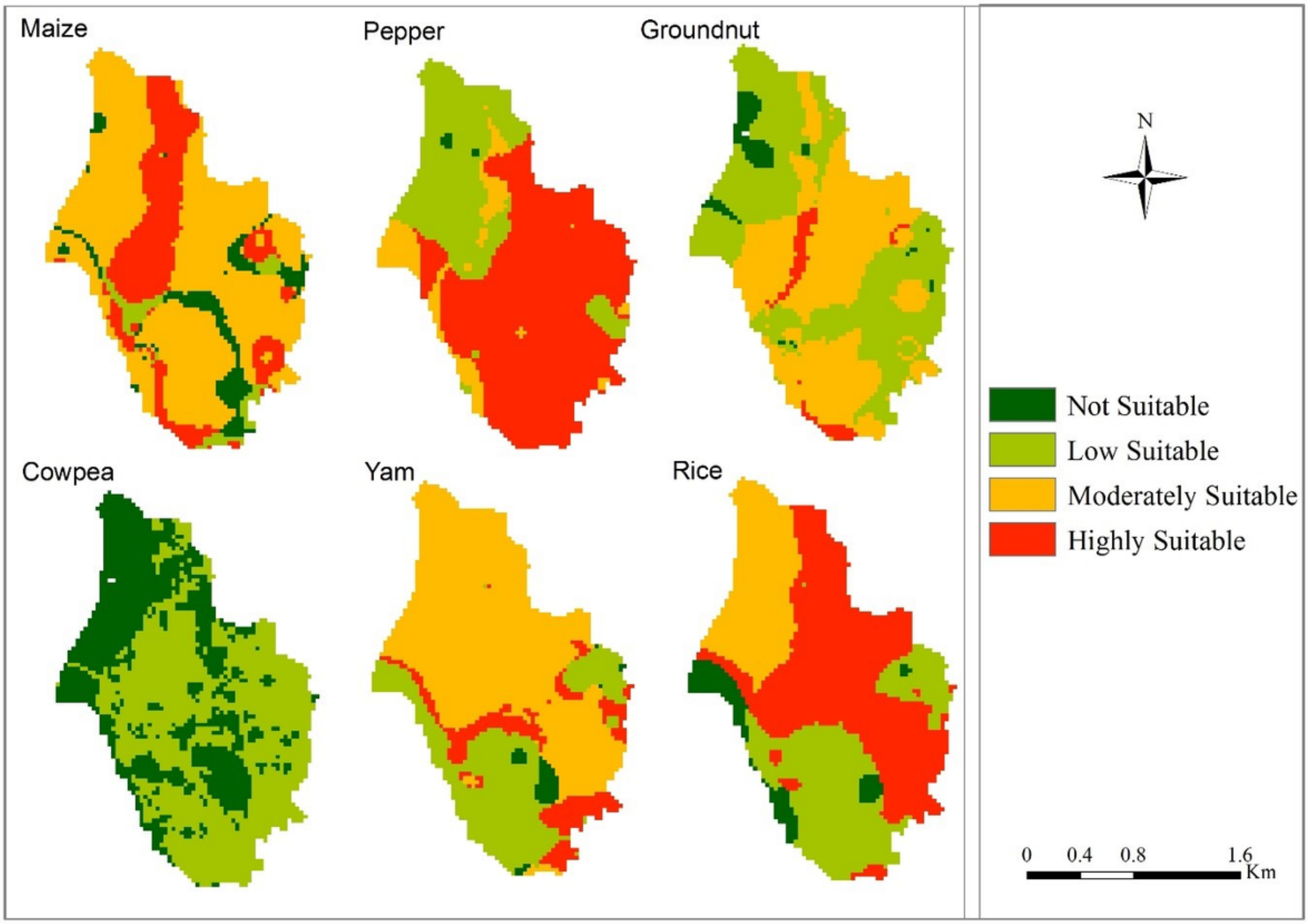
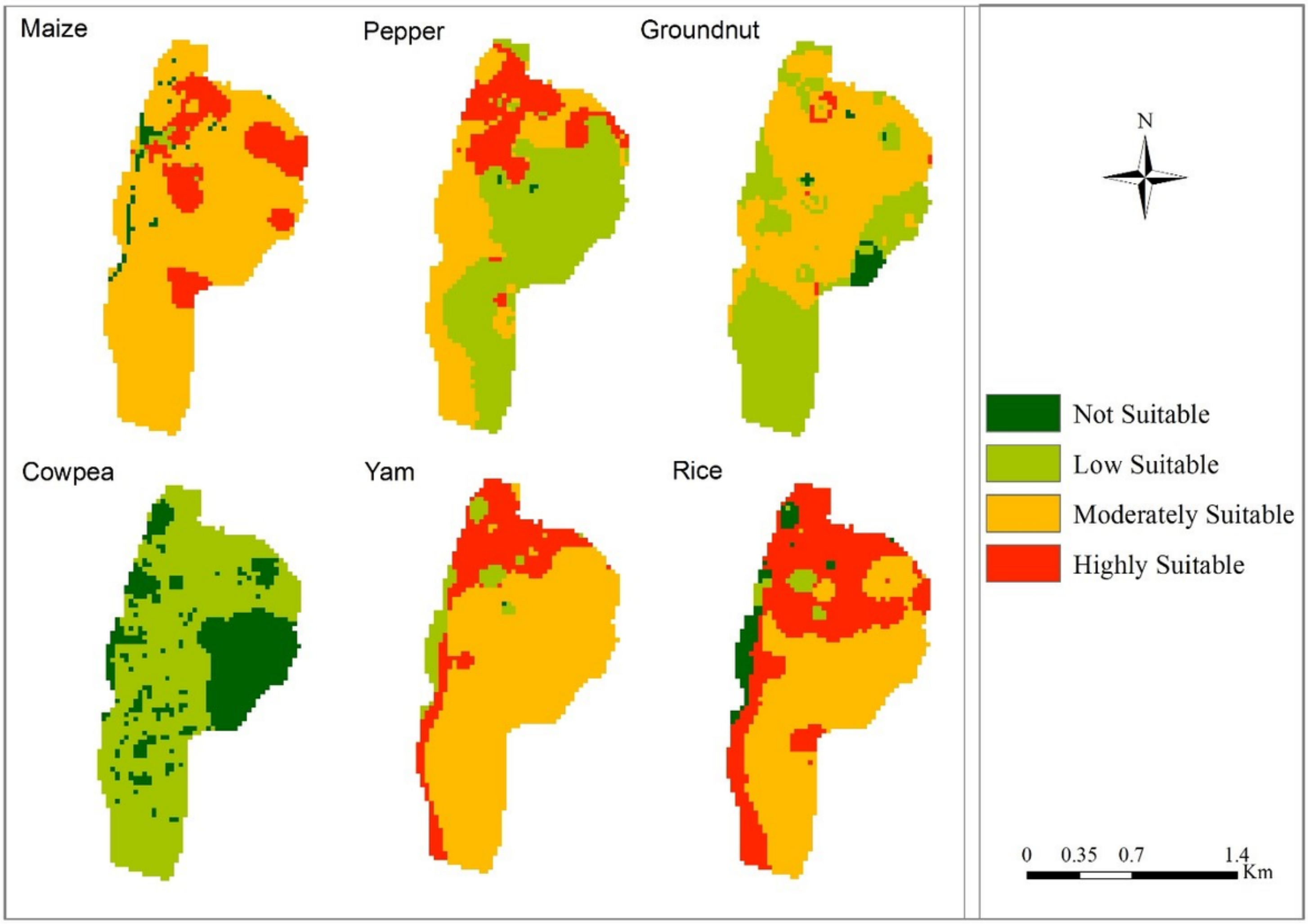


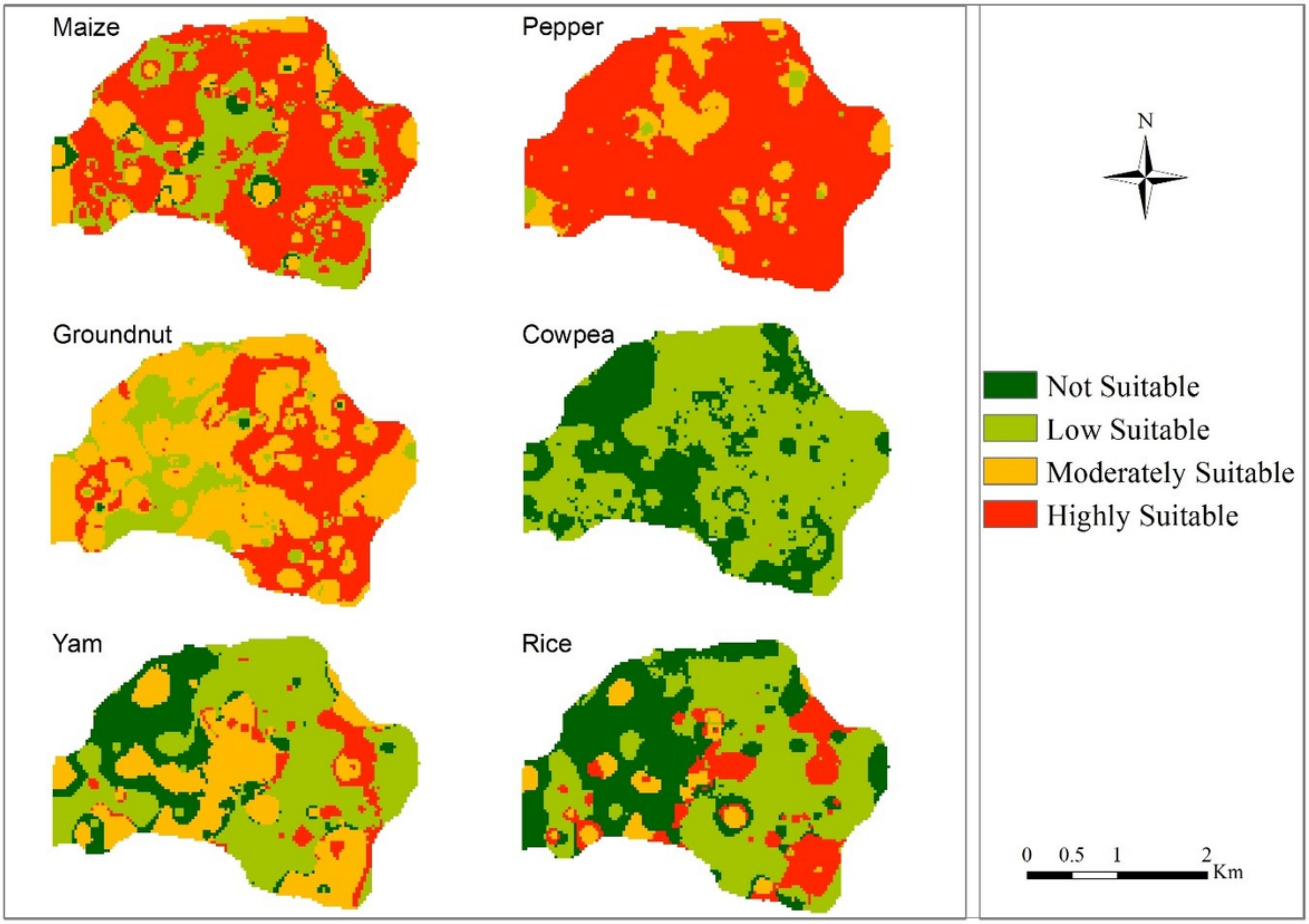

**Figure 7**

Agricultural Land Suitability Map for Crop Production in Zagua



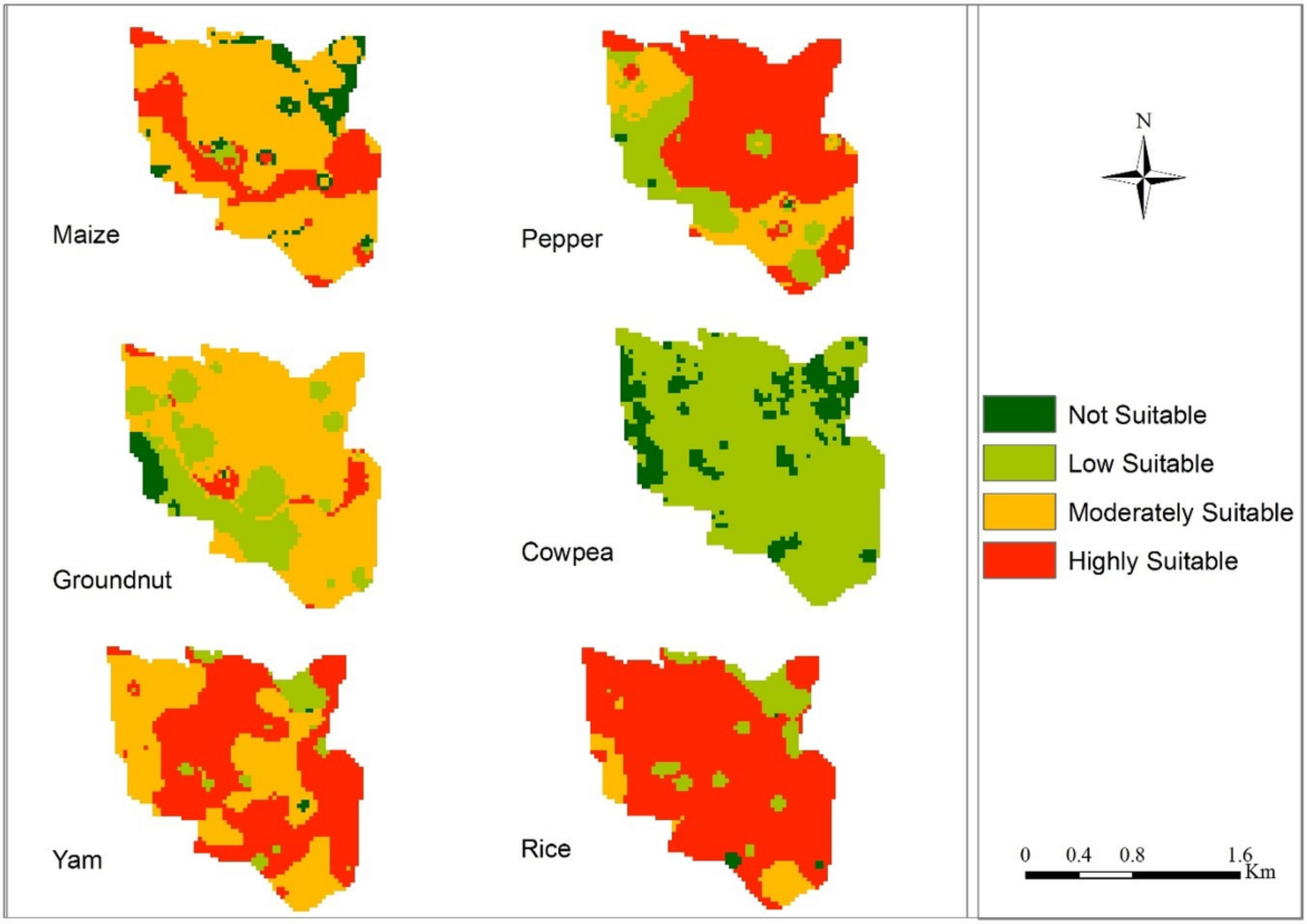

## Figure 8

Agricultural Land Suitability Map for Crop Production in Cheshegu




## Figure 9

Agricultural Land Suitability Map for Crop Production in the Yoggu




## Figure 10

Agricultural Land Suitability Map for Crop Production in the Daboasdhie