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Investigating rural poverty and marginality in Burkina Faso using remote sensing-based products

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ABSTRACT

Poverty at the national and sub-national level is commonly mapped on the basis of household surveys. Typical poverty metrics like the head count index are not able to identify its underlaying factors, particularly in rural economies based on subsistence agriculture. This paper relates agro-ecological marginality identified from regional and global datasets including remote sensing products like the normalized difference vegetation index (NDVI) and rainfall to rural agricultural production and food consumption in Burkina Faso. The objective is to analyze poverty patterns and to generate a fine resolution poverty map at the national scale. We compose a new indicator from a range of welfare indicators quantified from Georeferenced household surveys, indicating a spatially varying set of welfare and poverty states of rural communities. Next, a local spatial regression is used to relate each welfare and poverty state to the agro-ecological marginality. Our results show strong spatial dependency of welfare and poverty states over agro-ecological marginality in heterogeneous regions, indicating that environmental factors affect living conditions in rural communities. The agro-ecological stress and related marginality vary locally between rural communities within each region. About 58% variance in the welfare indicator is explained by the factors of rural agricultural production and 42% is explained by the factor of food consumption. We found that the spatially explicit approach based on multi-temporal remote sensing products effectively summarizes information on poverty and facilitates further interpretation of the newly developed welfare indicator. The proposed method was validated with poverty incidence obtained from national surveys.

1. Introduction

Subsistence farming is an important agricultural practice in many African states. For instance, in Burkina Faso approximately 92% of the country workforce is actively associated with the agricultural sector, of which 80% are small holder farmers who live in rural areas and have less than 1 ha of land (USAID, 2009). Agricultural production is largely constrained by a range of biophysical factors related to soil properties, rainfall and water availability (West et al., 2008). The agro-ecological conditions vary spatially and respond to a highly local physical environment. In Burkina Faso, more than 80% of the total population lives in rural areas, of which 94% is considered poor (USAID, 2009). The lack of local infrastructure often restrains rural households to apply sustainable farming practices since it limits the farmer's access to market and services (Alasia et al., 2008; Gatzweiler et al., 2011). This suggests that rural poverty in Burkina Faso can be related to the agricultural productivity and that it can be characterized from the spatial distribution of agro-ecological potential.

Traditionally, poverty as opposite to welfare is mapped by analyzing a range of socioeconomic factors obtained from targeted household surveys. Such surveys assess household capital assets, e.g. income, expenditure, food consumption, and other living conditions. Using these, indices are obtained to estimate the incidence of poverty. For example, the head count index (HCI) is the percent of the population in an area living below an established poverty line, i.e., a normative level of income or expenditure. To extrapolate these surveys towards an entire region, various small area estimation techniques have been developed (Hoddinott and Quisumbing, 2003; Benson et al., 2005). These techniques make predictions by relating the household welfare status from targeted household surveys to the household characteristics from national census, and apply the relation to households with same characteristics. A clear insight into the likely causes of the situation is often missing, because factors of marginality are not included during poverty mapping (Hyman et al., 2005; Robinson et al., 2007). Also, these techniques depend on the availability of national censuses that take place only once in several years due to their high operational costs.

To locate marginal areas, alternative approaches analyze environmental constraints (e.g., soil erosion, droughts) using remote sensing (RS) data and products (Parkins and MacKendrick, 2007; Alasia et al., 2008). Being able to acquire up-to-date data over a large area by utilizing the high spatial and temporal coverage

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provided by RS, these approaches can quantify the increased susceptibility of specific areas to become marginal due to extreme events of environmental constraints. However, the environmental approaches are primarily concerned with marginality and they rarely quantify its impact on livelihood status. Following this, Nelson et al. (2012) related RS products with household level expenditure obtained from survey data to explain the poverty patterns in Uganda. Although this approach advanced traditional poverty mapping, it is insufficient to interpret the observed relations, because a single aspect of poverty (e.g., income, expenditure, and other living conditions) is usually not enough to explain welfare and marginality, particularly in rural economies based on subsistence agriculture (Gatzweiler et al., 2011).

In this paper, a geographically explicit approach is presented for studying poverty and marginality at a fine resolution and over a larger area. We investigate both agro-ecological marginality from RS-based products and welfare and marginality from household conditions. By studying these conditions over a large area, we aim at better understanding the factors that determine household marginality. In this way, this paper advances current environmental procedures of poverty mapping creating a more dynamic method that can be effectively utilized by policy-makers to reduce poverty (Nelson et al., 2012).

In practice, our main objective is to use RS products and other regional data sets for extrapolating poverty quantified from the targeted household surveys. The study is illustrated using data from Burkina Faso where agricultural surveys are collected annually targeting only representative communities countrywide. We developed a composite index from several welfare aspects observed from household surveys. This index and the RS products are used to map poverty at the national scale.

2. Background

2.1. Study area

This study is conducted using data from Burkina Faso, which is ranked among the poorest countries of the world (USAID, 2009). Agriculture contributes to 31% of the GDP and to 60% of the exports that are the main source of growth of the national economy. The livestock sub-sector accounts for 25% of agricultural GDP and 8% of total national GDP (USAID, 2009). Several environmental and socio-economic factors affect agricultural production like the spatial variation in both frequency and intensity of rainfall during the crop growing season (West et al., 2008). Administratively, the country is divided into 13 regions and 351 districts, which are split in about 7000 rural communities. The term terroir refers to a rural community in which small-holder farmers make their livelihood (AGRISTAT, 2010). A terroir is a well-defined land management system which not only constructs a physical area, but also a social construct and the notion of natural resources and biophysical conditions. Thus, it constitutes a communal farming system in which farmers contribute their individual parcels and adopt common policies for agricultural production. In this study, we used terroir community as the level to quantify poverty and marginality in Burkina Faso. AGRISTAT (AGRISTAT, 2010) conducts targeted household surveys for one representative terroir community per district.

The head count index (HCI) is available for 1994, 1998, 2003 and 2009. In 1994, the country's first surveys for household living conditions were conducted on the basis of agro-climatic regions. Later in 1998, they shifted to the administrative regions. The HCI was compiled based on the poverty line of 1 USD (United States Dollar) adult^{-1} day^{-1}. In 2010, HarvestChoice compiled HCI maps (gridded) from surveys carried out between 1998 and 2003 by establishing a poverty line of 1.25 USD adult^{-1} day^{-1} (Wood et al., 2010). These studies consistently show that the North, South Central, Central Plateau, Boucle du Mouhoun, East Central, and Southwest regions are typically affected by poverty, with a rate of incidence well above the national average (Fig. 1). The HCI is close to the national average in the West central, Eastern, and Cascades regions, whereas the other regions are relatively less affected by poverty.

2.2. Mapping communal welfare in Burkina Faso – our approach

This study defines marginality as a function of cause–effect relations between stressor and asset variables. Stressors are often exogenous factors that directly or indirectly affect the agricultural production of rural communities (Alasia et al., 2008). In this study, the agro-ecological stress on rural communities was characterized by analyzing RS products as explained in Section 3.1. To quantify the impact of RS-based stressors on communal welfare status, we focused on household assets related to the agricultural outcomes in a rural community. The asset variables were obtained from Georeferenced household surveys as explained in Section 3.2. A rural community was considered to be marginal if it encountered high stress on agricultural production, eventually resulting into low household assets. Therefore, to quantify communal welfare and marginality at the national scale, the stressor and asset variables were linked by using spatial regression as explained in Section 3.4. To quantify poverty and marginality, we made the following assumptions:

1. A high agricultural production in rural Burkina Faso helps to increase farmers welfare in that they can meet daily food requirement: poor farmers will suffer from food insecurity and food insecure farmers will be poor farmers (de Graaf et al., 2001).
2. Households in a rural community combine individual lands for cultivation and face similar agro-ecological and socioeconomic conditions (Bigman et al., 1999). Farmer's marginality therefore vary considerably between the rural communities and only to a lesser degree result into income differences between individuals within communities.
3. We define four levels of marginality: high marginal, low marginal, low welfare, and high welfare. The agricultural production in rural communities, and consequently, the intensity of poverty and food insecurity decreases from high marginal to high welfare levels.

3. Materials and methods

3.1. Extraction of stressor variables

The following stressor variables were derived from RS data:

The normalized difference vegetation index (NDVI), calculated as $(\mathrm{NIR}-R)/(\mathrm{NIR}+R)$, where NIR is the spectral reflectance in the near-infrared where canopy reflectance is dominant, and R is the reflectance in the red portion of the electromagnetic spectrum where chlorophyll absorbs strongly (Tucker, 1979). NDVI has been used to estimate leaf area, percentage cover and biomass. Therefore, NDVI variability may be linked to the factors that limit plant growth. The limiting factors of plant growth (i.e. stressors on agricultural production) may be poor soils, limited water availability, etc. Therefore, in this paper, NDVI has been considered as a measurement of amalgamated plant growth that reflects various stresses on agricultural production. For 2009, a time series of SPOT VEGETATION NDVI composite (S10) products were obtained from (Joint Research Centre, 2012). This product is derived from 10-day data and mapped onto a 1 km latitude–longitude grid.

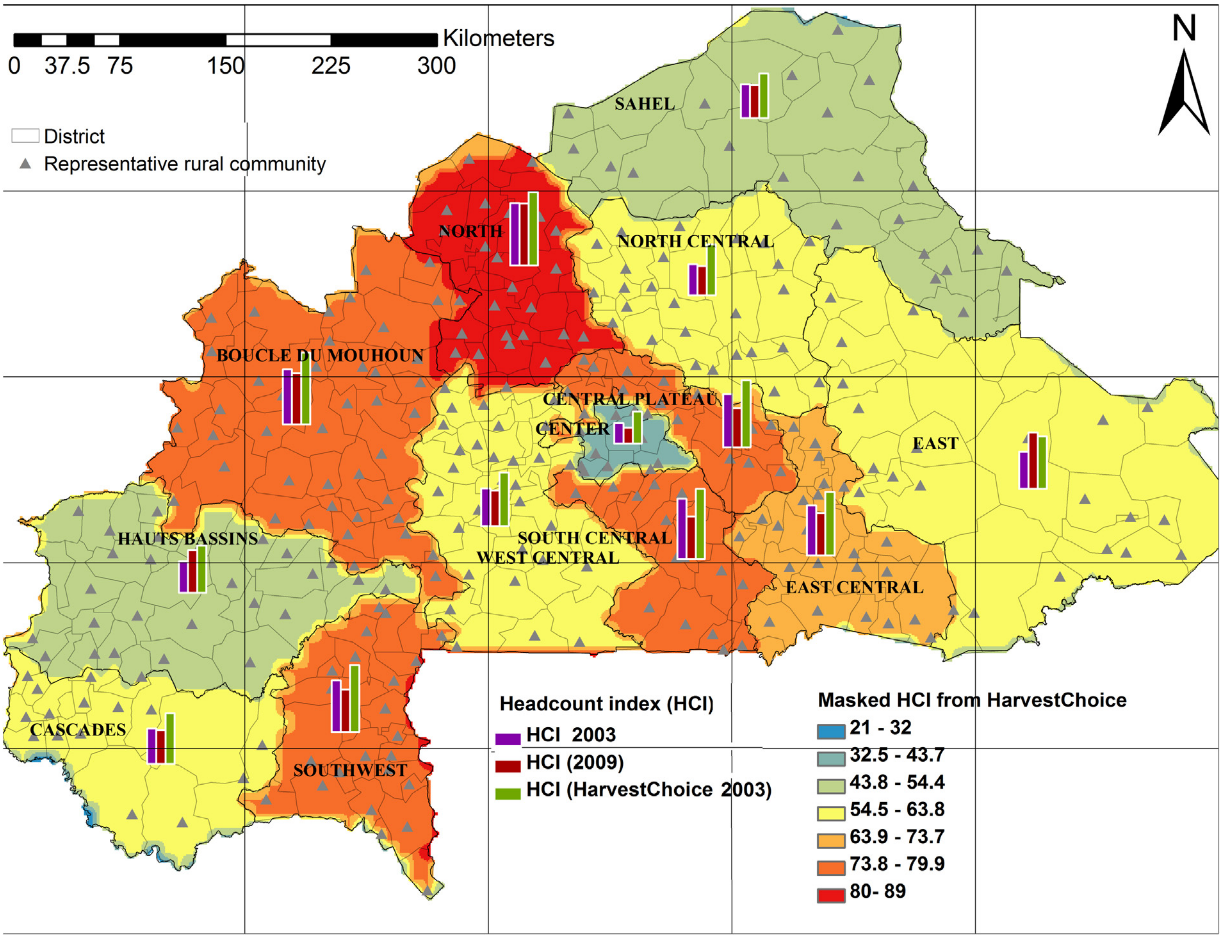

Fig. 1. Mean head count index (HCI) for the 13 administrative regions of Burkina Faso, calculated from country's national surveys of 1994, 1998, 2003 and 2009; and from HarvestChoice data.

The intensity and spatial distribution of rainfall poses a significant climatic stress on the agricultural production. A series of 10-day tropical applications of meteorology using satellite (TAMSAT) images was acquired to extract the climatic stress on agricultural production for 2009. The TAMSAT rainfall estimates (RFE) have been validated for West Africa and the Sahel region using a dense rain gauge network covering area of 1° square (Grimes et al., 1999). For 10-day TAMSAT RFE, 85% of the estimated and measured values agree to within 1 standard error for 1° square.

The agro-ecological stress in rural communities was characterized by analyzing NDVI and RFE time series. To reduce amount of data, we applied the harmonic analysis of time series (HANTS) algorithm (Verhoef, 1996) to the SPOT and TAMSAT time series. Like this, each time series can be described by three Fourier components (three amplitudes and two phases). More details on HANTS parameterization are provided in Appendix A.

In addition RS-based gridded products were analyzed as potential long-term stressors on food production:

Length of growing period (LGP, days) characterizes agro-climatic constraints that relate potential productivity of lands with the average daily temperature and surface water balance. The areas of shorter LGP bear a long-term high stress from dry conditions. LGP data (1 km spatial resolution) obtained from (HarvestChoice, 2012) is based on 1960–1995 data from (IIASA/FAO, 2012). Soil data (1 km) showing the degree to which soil properties exert stress on agricultural production (LASC, land areas with soil constraints) were obtained from (FAO, 2012). Topographic data (1 km) of elevation (ELEV, meters) and slope (SLOPE, 0–90 integer degrees) were obtained from HYDRO1k data sets of (USGS, 2012). The slope data layer describes the maximum change in the elevations between each cell and its eight neighbors.

Besides these short and long term environmental factors, population density and market access are considered known stress factors of per capita food and agricultural production and consumption in sub-Saharan Africa (Dreschel et al., 2007). We obtained population density data (PD, people per km^2) from (HarvestChoice, 2012). We calculated the market access as a Euclidean distance (MARKD, meters) from rural communities to the major trade markets of food commodities (cereal and livestock) in Burkina Faso. Furthermore, most of people living in the northern half of Burkina Faso are agro-pastoralists. Poor households, particularly women, generally contribute labor to keep poultry and small livestock (e.g. goat, sheep) (USAID, 2009). We obtained data on poultry and small livestock (livestock per km^2) from (HarvestChoice, 2012). All spatial data were clipped and/or resampled to a common grid of a 1 km spatial resolution.

3.2. Extraction of asset variables

Asset variables were extracted from the country's agricultural surveys carried out in 2009. AGRISTAT surveys all households in the representative rural communities (AGRISTAT, 2010). Asset variables were obtained from data of all households belonging to a representative rural community. In total 3540 households were surveyed to cover the 303 districts of the country. The following five asset variables were derived:

- Percentage of household members employed in farming activities (HME). Both paid and non-paid works were considered. Paid household members work in various farm and livestock activities and get wages in the form of food or cash, whereas non-paid members participate in activities without any compensation, e.g. women/child as family or collective labor.
- Agricultural production of each household (AGPROD), obtained as the projected crop grains (kg) for the current crop season. AGRISTAT asks farmers to make this projection considering the vegetative performance of the crops at the household parcel level.
- Household stocks (STOCKS) left from the previous crop season, obtained as observed crop grains (kg).
- Number of animals (e.g. bulls, donkeys) owned by each household (NA).
- Household food consumption (CONSUM), calculated as the minimum dietary energy consumption (kcal) per household member per day. AGRISTAT records number of food servings consumed by a household member in the last seven days. We considered that the consumed food was obtained from any source, e.g. self-produced, purchased, obtained as wage compensation, or donated.

We assume that high values of these household asset variables show high agricultural outcomes in a rural community, and consequently, the community has encountered a high welfare level or low intensity of poverty and food insecurity.

3.3. Developing a composite communal asset index

A weighted combination of the five chosen asset variables was made to compute a communal composite asset index (CAI). As these assets have a skewed distribution and are potentially highly correlated, the following procedure was applied.

First, we transformed the asset variables using the logarithmic function to remove skewness from the raw data. Second, to account for their different measurement units, this transformation was followed by a normalization to a common measurement scale using the Min–Max method (Ebert and Welsch, 2004):

$$I_y = \frac{y - y_{\min}}{y_{\max} - y_{\min}}; \quad y_{\min} < y < y_{max} \tag{1}$$

Here I_y is the normalized variable of the log-transformed asset variable y, $y_{\min}$ and $y_{\max}$ are the minimum and maximum of y across all rural communities. Extreme minimum and maximum values were examined for outliers in order to avoid negative effects on the subsequent analysis. Third, a minimum residual factor analysis was applied to capture non-overlapping information between the correlated asset variables (Berlage and Terweduwe, 1988). This analysis groups the asset variables according to their degree of correlation. Subsequently, an ordinary least squares (OLS) regression was applied to adjust the eigenvalues of the correlation matrix to minimize the off diagonal residual correlation matrix. The minimum number of factors to retain for the factor analysis was decided based on Horn's parallel analysis (Horn, 1965). In this analysis, the minimum residual solution was transformed into an oblique solution using the oblimin method of rotation. Within each of these factors, all asset variables were weighted to reflect the proportion of their variance over the study area which is explained by the factor. The weights were obtained by squaring and normalizing the estimated factor loadings.

3.4. Linking CAI and the stressor variables

We used geographic weighted regression (GWR), a spatial regression technique, for which the 303 CAI values were the independent variable and the values of the stressors were the explanatory variables. Being an extension of global regression techniques such as ordinary least square (OLS) (Fotheringham et al., 2002), GWR identifies and models spatial non-stationarity, i.e., spatially varying relationships to present a significant improvement over a global regression (Leyk et al., 2012). We therefore, first, computed OLS as a 'baseline' global model to test statistical significance of the coefficients for each explanatory stressor variable and to test the model residuals for spatial autocorrelation and clustering.

Let a set of observations of CAI be denoted as CAI(s_1), CAI(s_2),. . ., CAI(s_n), where s_i is location of a rural community (i.e. representative community per district), and n is the number of observations. The global regression can be expressed as,

$$\text{CAI}(s) = \beta_0 + \sum_k \beta_k X_k(s) + \epsilon_s, \tag{2}$$

where β_0 is the intercept, β_k represent the estimated coefficients for explanatory stressor variables X_k, $X_k(s)$ is the value of the variable X_k at location s and ϵ_s denotes the random error term for location s. We selected stressor variables that were significant ($p < 0.05$), tested them for impact of multicollinearity on the estimation precision of regression coefficients (Neter et al., 2005), and calculated the Akaike information criterion (AIC) (Hurvich et al., 1998). Clusters of high and low residual values at the representative community level may indicate spatial variation in the CAI relationship. We tested for significant local clusters in model residuals based on local indicators of spatial associations (LISA) (Anselin, 1995) using Rook contiguity (i.e. two representative rural communities are neighboring if their districts share common borders, see Fig. 1) for creating the spatial weights matrix. Moreover, we computed the bivariate LISA to check the co-variation of the value of CAI at a given representative community with the average of neighboring values of each of the selected stress factors.

Geographic weighted regression establishes separate models for each sampled location (Fotheringham et al., 2002), and therefore allows for estimating locally the regression coefficients to account for spatial variation of these coefficients across a given study area (Gao et al., 2003). This changes the model in Eq. (2) to,

$$\text{CAI}(s) = \beta_0(s) + \sum_k \beta_k(s) X_k(s) + \epsilon(s), \tag{3}$$

where $\beta_0(s)$ and $\beta_k(s)$ represent the model local estimates of intercepts and coefficients at a location s, and $X_k(s)$ are stressor variables. The model estimates local coefficients from $\hat{\beta}_{GWR}(s) = (X^T W(s) X)^{-1} X^T W(s).CAI(s)$, and $W(s)$ is a $n \times n$ diagonal matrix of spatial weights specified with a spatial kernel function. The kernel centers on a rural community location s, and weights the surveyed values on neighboring locations t subject to a distance decay. We used the Gaussian weighting as kernel function such that,

$$W_{st} = \exp\left[-0.5\left(\frac{d_{st}}{b}\right)^2\right], \tag{4}$$

where d_{st} is the distance between the sth and Sth rural community locations (i.e. a spatial neighborhood), and b is the kernel bandwidth that measures the distance-decay in the kernel function. A bandwidth can be specified as global, i.e., the same kernel size at each location, or as adaptive bandwidths that vary in size.

The spatially non-stationary relationships in GWR may vary according to the spatial scales of each stressor variable on CAI. This scale-dependency largely demands for finding an optimal kernel size for local estimation in GWR. For this, the most common approaches, i.e., cross-validation or minimizing the Akaike's information criterion (AIC) (Hurvich et al., 1998) may not sufficiently determine an effective bandwidth for model fitting and performance (Leyk et al., 2012). We tested the effect of spatial scale of local relationships on the stability and multicollinearity of GWR

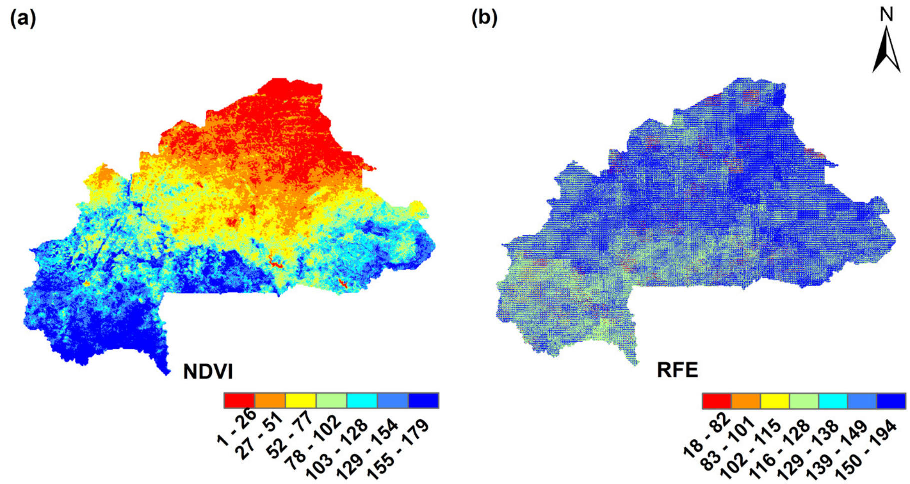

Fig. 2. Mean components of harmonic analysis of time series (HANTS) algorithm applied to image series: (a) the normalized difference vegetation index (NDVI), and (b) the tropical applications of meteorology using satellite (TAMSAT) rainfall estimates (RFE).

coefficients. By increasing stepwise the GWR adaptive bandwidth measures ($0.05 = 15n$, $0.1 = 30n$, $0.15 = 45n$, $0.2 = 60n$, $0.25 = 75n$, and $0.3 = 90n$, where n is the number of neighboring rural communities), we investigated the effect of increasing spatial neighborhood on local estimation. For each increment, we recorded AIC value and spatial stationarity index (Fotheringham et al., 2002), which is a ratio between the interquartile range for GWR coefficients and twice the standard error (SE) of the same variables from the equivalent global model. We selected adaptive proportion of rural communities, for which (i) the AIC score was minimum, and (ii) the variance of the stationary index for all stressor variables were larger within an effective spatial scale (Gao et al., 2003).

We compared the performance of the local and global models based on AIC and adjusted-R^2 values, and performed ANOVA F-test. Moreover, Moran indexes (Moran's I) of residuals were computed to compare the ability to deal with spatial autocorrelation between OLS and GWR.

We applied GWR as a local spatial prediction model to predict CAI at unsampled locations as,

$$\widehat{\mathrm{CAI}}(s_0) = X_0{}^T . \hat{\beta}_{\mathrm{GWR}}(s), \tag{5}$$

where X_0 is the vector of p stressor variables at an unsampled location s_0, $\hat{\beta}_{\mathrm{GWR}}$ is the vector of $p+1$ estimated drift model coefficients. We evaluated the GWR performance by using the following methods that quantify differences between the observed and predicted CAI values:

1. We computed histogram descriptive statistics to describe the observed and predicted CAI distributions.
2. We calculated mean absolute errors (MAE), mean square errors (MSE), and root mean square error (RSME) to compare the differences between the CAI observed in the AGRISTAT data and the GWR predicted CAI.
3. Although the HarvestChoice HCI data have a sufficient spatial resolution for validating the predicted CAI, these were however based on the country's 1998–2003 surveys (Wood et al., 2010). Alternatively, the HCI data obtained from the country's 2009 national surveys of household living conditions were available only for the administrative regions. We used this latter choice as an independent data source for validation and calculated the CAI averages for the 13 Burkinabé regions. Furthermore, the predicted CAI values vary from 0 to 1 such that the lower index values represent a low assets level and/or a high stress level. Whereas, HCI ranges 0–100 such that the lower index values represent a low poverty level. We therefore transformed CAI into what we called the composite poverty index (CPI) as, $\mathrm{CPI}(s) = (1 - \mathrm{CAI}(s)) \times 100$, where s is a location.

4. Results

4.1. Extraction of stressor variables

Fig. 2 shows the output of HANTS algorithm (only mean components) that contributed significantly to explain CAI. The HANTS algorithm reduced the RS data from 36 decadal images of an image series to 7 amplitude-phase datasets, i.e., single amplitude and phase images for each frequency, where the zero-frequency (mean) is without a phase. Based on RFE phase datasets we differentiated the three seasons: wet season May–September (78–179), post-wet season October–November (77–129), and dry season December–April (1–51). High inter-season difference of rainfall indicates an extreme dry period for vegetation during which households usually depend on stocks. The RFE amplitude datasets showed a high spatial variability of rainfall intensity, with a low and declining rainfall in the North as compared to the higher but more homogeneous rainfall in the South. Consequently, the mean NDVI signal (Fig. 2a) shows a North–South directed increasing trend of vegetation performance. Given the limited use of irrigation in Burkina Faso, thus the northern communities have low potential for household food production and stocks.

4.2. Extraction of asset variables

Table 1 shows average community assets (raw data) aggregated from the household survey data of representative rural communities belonging to the 13 Burkinabé administrative regions. The asset variables AGPROD, STOCKS, CONSUM, and NA show high variation among the different regions. The average HME however is not significantly varying for the different regions and is approximately equal to the country mean (78%). The STOCKS variable shows that only a low percentage (5–10) of the total surveyed households is able to meet consumption requirements from their food stocks. The scatterplots of all with all asset variables show a high level of correlation among the asset variables (Fig. 3). The logarithmic transformation successfully reduced the observed skewness from the asset variables, from the observed skewness in the (1.63–3.08) range to the (−0.09 to −0.2) range.

Table 1
Community average assets (raw data) aggregated from the household data of 303 surveyed rural communities belonging to the 13 Burkinabé regions.

Region	*n*[a]	Mean HME[b]	Mean AGRPROD[c]	Mean STOCKS[d]	Mean NA[e]	Mean CONSUM[f]
Boucle du Mouhoun	43	77.7	41,420.3	179.8	40.53	1206
Cascades	15	78.2	49,574.5	266.6	33.66	1545.8
Center	9	84.1	10,900.8	147.3	17.3	574.33
East Central	23	75.3	23,352.7	243.7	46	1018.3
North Central	27	67.6	14,748.6	161.6	31.5	639.1
West Central	30	82.1	32,836.2	295	35	1190.7
South Central	17	81.5	16,984.1	250	43.2	977.1
East	22	78.2	26,248.4	198.8	50.9	1189.3
Hauts Bassins	28	76.3	54,198.6	193	35.1	1326.5
North	25	76.2	21,212.1	302.2	32.7	988
Central Plateau	18	76.4	21,940.5	336.8	43.8	741.5
Sahel	22	77.9	11,629.7	50.4	34.9	1000.2
Southwest	24	81.4	46,052.7	194.9	38.8	1199.8

[a] Number of surveyed rural communities in region.
[b] Household members employed in farming activities (%).
[c] Crop production (kg of grains) of households for the current crop season.
[d] Household stocks (kg of grains) left from the previous crop season.
[e] Number of animal owned by household.
[f] Minimum dietary energy consumption (kcal) per household member per day.

4.3. Developing a composite communal asset index

The assets variables were combined into the communal composite asset index (CAI) using a minimum residual factor analysis. The results of such an analysis are presented in Fig. 4(a and b) and in Table 2. These results show that the 5 asset variables are correlated with 2 minimum residual factors with proportion variances equal to 0.33 and 0.24, respectively, thus accounting for 57% of the total variance. Using the rotated factor loadings, the asset variables were aggregated into factor-specific scores (Fig. 4b). The first minimum residual factor (MR1) has loadings on the asset variables that present patterns of crop and livestock production, whereas rotated factor loadings from the second minimum residual factor (MR2) are projected mainly on the household food consumption patterns across the rural communities. The squared factor loadings represent the proportion of the total unit variance of the assets which is explained by the factor. MR1 accounted for 42%, 35%, and 20% of the variance in the values of STOCKS, NA, and AGRPROD assets, whereas MR2 accounted for 88% and 0.01% of the variance in the CONSUM and HME values, respectively. A small contribution of HME can also be justified on the bases of summary statistics of raw data in Table 1, showing a low variation of the asset variable over the entire country. The resulting factor-specific scores are aggregated into the CAI by weighting each factor according to its relative contribution to

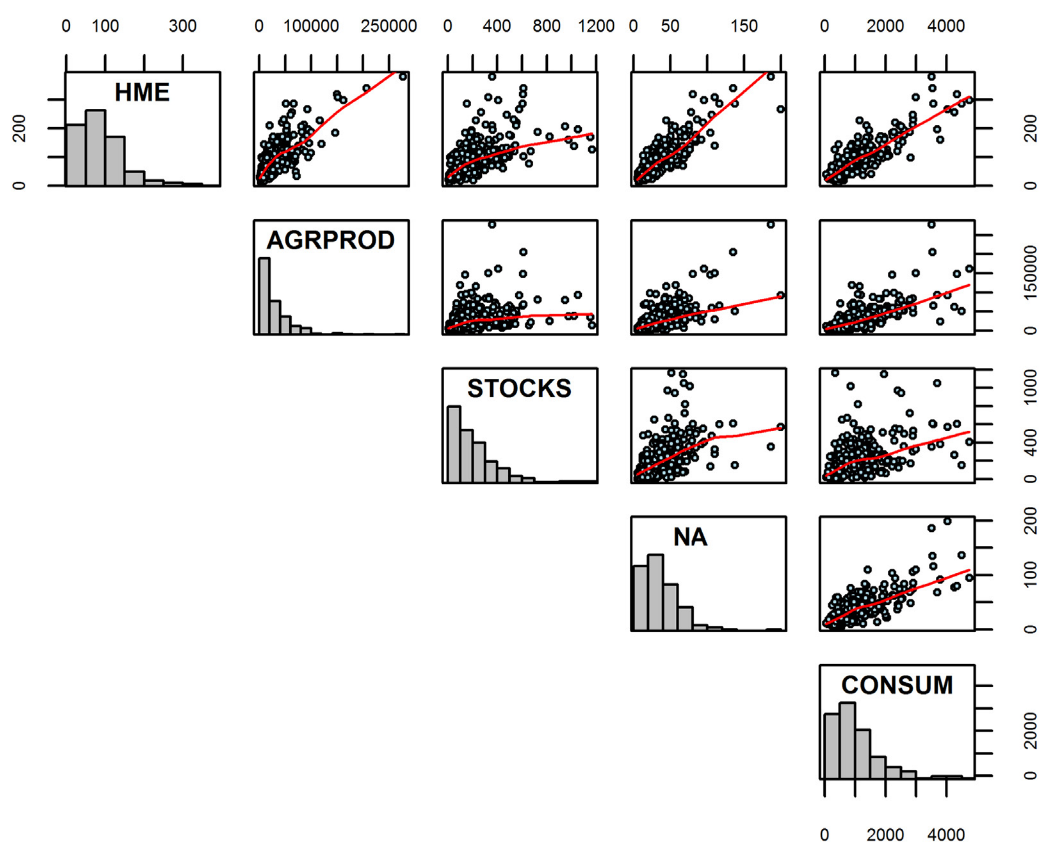

Fig. 3. Scatterplots of household assets derived from AGRISTAT data: household members employed (HME), households crop production (AGRPROD), household stocks (STOCKS), number of animal owned by household (NA), and minimum dietary energy consumption (kcal) per household member per day (CONSUM).

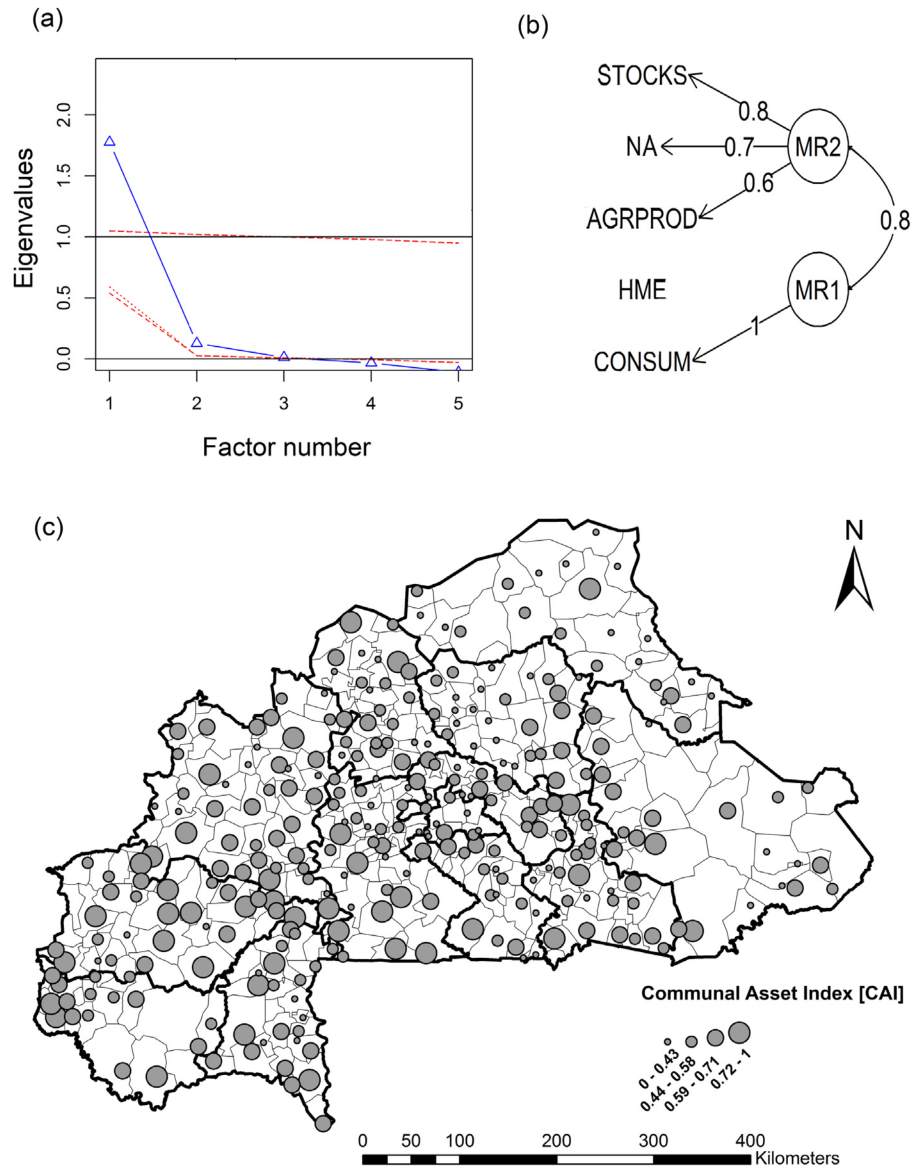

Fig. 4. Minimum residual factor analysis – (a) eigenvalues (on vertical axes) express the proportion of the total variance in the data explained by each factor, and (b) minimum residual factors (MR1 and MR2) standardized values of the individual assets multiplied by their individual weights; household members employed (HME), households crop production (AGRPROD), household stocks (STOCKS), number of animal owned by household (NA), and minimum dietary energy consumption (kcal) per household member per day (CONSUM) – (c) spatial distribution of the communal composite asset index (CAI) observations at 303 surveyed rural communities.

the overall variance with MR1 and MR2 explaining the 58% and 42%, respectively. Crop and livestock production obtained a slightly higher weight than food consumption.

Fig. 4(c) shows the spatial distribution of CAI. As defined in Section 2.2, the resulting CAI values were classified into four intervals from high marginal to high welfare. In general, marginal communities fall within the first two levels where the first level (CAI = 0–0.43) represents a severe marginality and the second level (CAI = 0.44–0.58) represents a high marginality, whereas the next two levels (CAI = 0.59–0.71) and (CAI = 0.72–1) represent low marginal and high welfare communities, respectively. High marginal communities mostly correspond to the regions of Boucle du Mouhaun, North, North Central, South Central, East Central, Center, Central Plateau, and Sahel. In the Cascades and Haut Bassins areas, most communities fall within the low marginal range, whereas the Southwest, West Central, and Eastern regions have both low and high marginal communities (see Fig 1 for the names of the regions).

4.4. Linking CAI and the stressor variables

Table 3 shows results from the global OLS model using the stressor variables that significantly ($p = 0.05$ to $p < 0.0001$) contributed to explaining the CAI variation. Agro-ecological stressor variables, both short-term (i.e. NDVI, RFE during the 2009 crop growing season) and long-term (i.e. LGP, LASC, SLOPE) consistently showed a significant agro-ecological stress ($p < 0.05$ to $p < 0.001$) on the agricultural production potential in Burkina Faso. We observed no significant impact of multicollinearity (i.e. VIF ≤ 5 for all the stressor variables). We found highly significant global spatial autocorrelation in the model residuals (Moran's $I = 0.22$; $p < 0.001$) (Fig. 5a). We also observed significant local clusters of low and high model residuals based on LISA – suggesting statistically significant clusters of over- and underestimations in the South, Center and in the North Burkina Faso, respectively (Fig. 5b).

The LISA maps in Fig. 6(a–f) illustrate spatial associations between CAI and the six selected stressor variables, NDVI, RFE,

Table 2
Rotated factor loadings and factor-specific scores for individual assets in the communal composite asset index (CAI).

	Factor 1		Factor 2	
Interpretation	Crop and livestock production		Food consumption	
Variables of individuals assets	Factor loadings	Weights[a]	Factor loadings	Weights
STOCKS[b]	0.81	0.42	−0.12	0.01
NA[c]	0.74	0.35	0.13	0.02
AGRPROD[d]	0.56	0.20	0.27	0.07
HME[e]	0.18	0.03	−0.12	0.01
CONSUM[f]	0.02	0	0.98	0.88
Weight of factors in CAI[g]		0.58		0.42
Selection criteria:				
Eigenvalues		1.67		1.20
Test-statistics:				
Chi-square				$p < 0.05$

[a] Normalized squared factor loadings.
[b] Household stocks (kg of grains) left from the previous crop season.
[c] Number of animal owned by households.
[d] Crop production (kg of grains) of households for the current crop season.
[e] Household members employed in farming activities (%).
[f] Minimum dietary energy consumption (kcal) per household member per day.
[g] Normalized sum of squared factor loadings.

Table 3
Properties of the global and local estimates of stressor variables to explain the communal composite asset index (CAI) using ordinary least square (OLS) and geographical weighted regression (GWR).

Parameters	(r, p)[a]	OLS Ests.[b]	OLS Std. error[c]	Significance	VIF[d]	GWR local Est. range[e]
Intercept		0.476^{+0}	0.122^{+0}	0.0001	–	$+0.411^{+0}$ to $+0.756^{+0}$
NDVI (mean)	(0.283, <0.0001)	-0.242^{-2}	0.846^{-3}	0.001	5	-0.454^{-2} to -0.168^{-2}
NDVI (amplitude 1)	(−0.033, 0.1)	-0.244^{-2}	0.106^{-2}	0.01	1.21	-0.334^{-2} to -0.105^{-2}
NDVI (phase 2)	(0.201, <0.001)	0.125^{-2}	0.498^{-3}	0.01	1.15	$+0.510^{-3}$ to $+0.360^{-2}$
NDVI (phase 3)	(0.148, <0.001)	0.235^{-3}	0.133^{-3}	0.05	1.11	$+0.110^{-4}$ to $+0.338^{-3}$
RFE (amplitude 2)	(0.061, 0.1)	0.168^{+0}	0.884^{-1}	0.05	1.38	$+0.115^{-1}$ to $+0.209^{+0}$
RFE (amplitude 3)	(−0.091, 0.1)	-0.113^{+0}	0.431^{-1}	0.001	1.4	-0.180^{+0} to -0.850^{-1}
LGP	(0.332, <0.0001)	0.304^{-2}	0.714^{-3}	<0.0001	5	$+0.137^{-2}$ to $+0.444^{-2}$
LASC	(−0.265, <0.0001)	-0.357^{-1}	0.160^{-1}	0.01	2.27	-0.665^{-1} to -0.189^{-1}
SLOPE	(0.119, 0.01)	0.525^{-3}	0.272^{-3}	0.05	1.11	$+0.287^{-3}$ to $+0.920^{-3}$
PD	(−0.116, 0.01)	-0.192^{-2}	0.100^{-2}	0.05	1.38	-0.427^{-2} to $+0.390^{-3}$
LIVESTOCK	(−0.159, 0.001)	-0.607^{-2}	0.137^{-2}	<0.0001	1.56	-0.797^{-2} to -0.257^{-2}
MARKD	(−0.018, 0.1)	-0.820^{-6}	0.450^{-6}	0.05	1.15	-0.218^{-5} to -0.926^{-6}

[a] Pearson correlations between the CAI and the stressor variables of the normalized difference vegetation index (NDVI), rainfall estimates (RFE), length of growing period (LGP), land areas with soil constraints (LASC), population density (PD), poultry and small livestock (LIVESTOCK), and distance to major trade markets (MARKD).
[b] Parameter estimates from OLS.
[c] Standard error.
[d] Variance inflation factor (VIF).
[e] Inter-quartile range of GWR local coefficients.

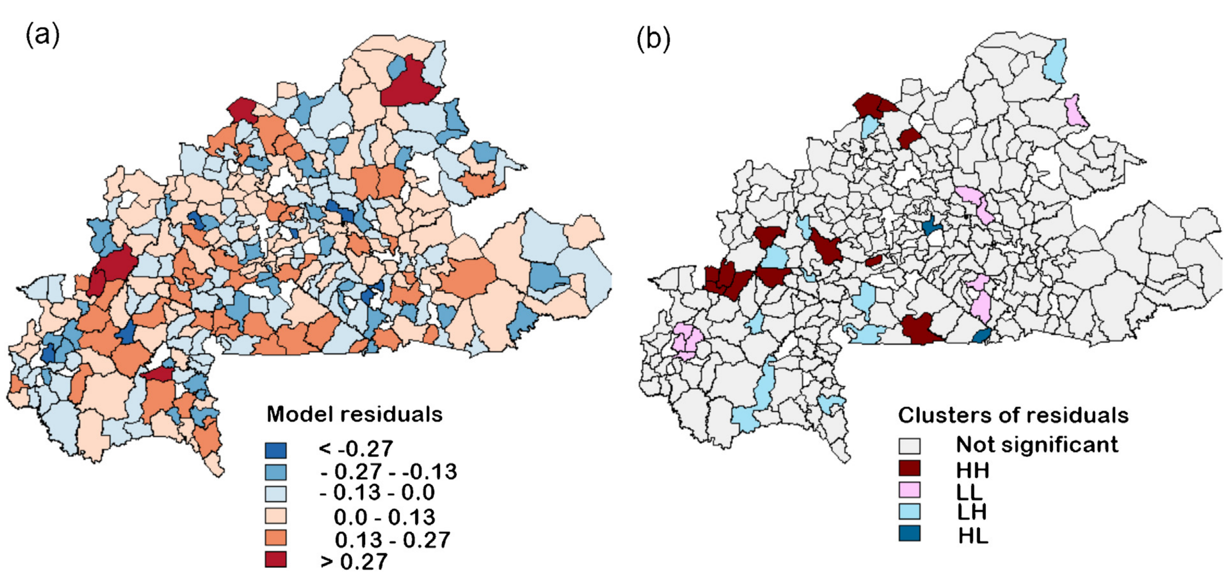

Fig. 5. (a) Spatial distribution of ordinary least square (OLS) residuals – (b) statistically significant local clusters of model residuals based on local indicators of spatial associations (LISA) analysis (HH – high values; LL – low values; HL and LH – outliers).

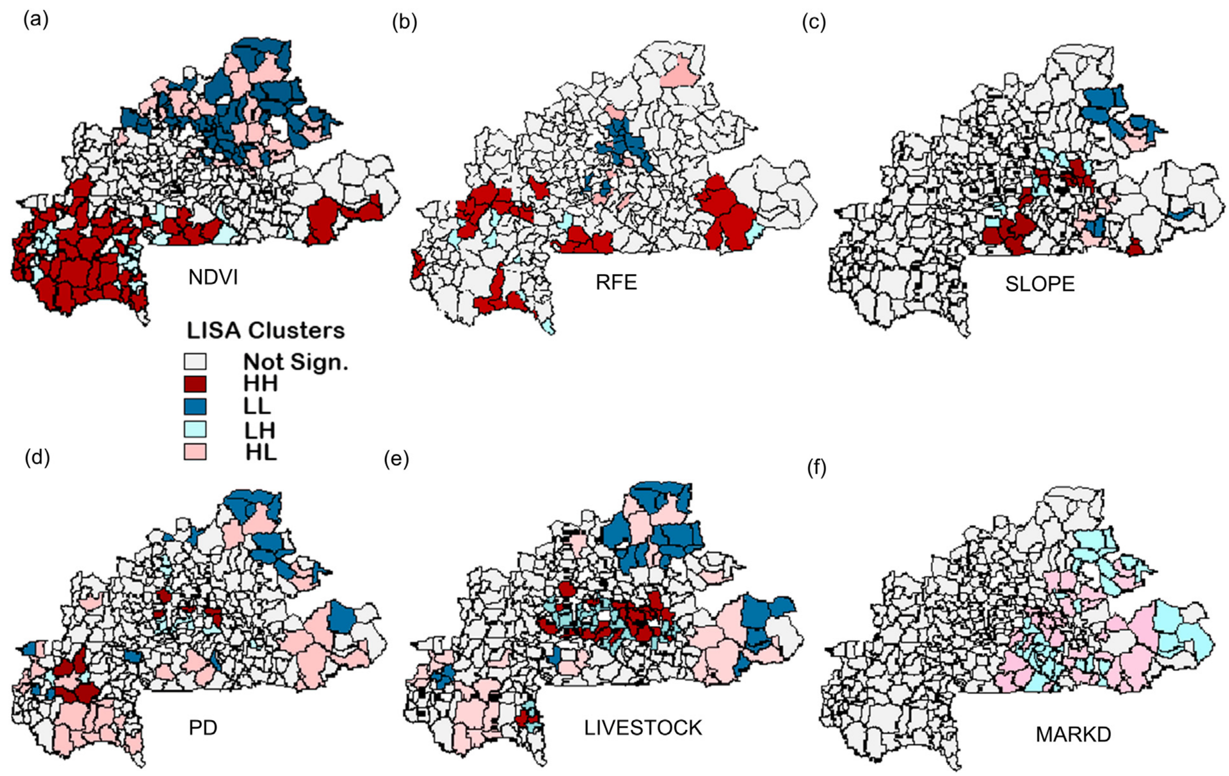

Fig. 6. Statistically significant ($p < 0.001$) spatial clusters from bivariate local indicators of spatial associations (LISA) analysis: using the communal composite asset index (CAI) and (a) the normalized difference vegetation index (NDVI), (b) rainfall estimates (RFE), (c) slope, (d) population density (PD), (e) poultry and small livestock (LIVESTOCK), and (f) market distance (MARKD) (HH high – high values; LL low – low values; HL and LH – outliers; first letter indicates CAI values, second one the stress factor).

SLOPE, PD, LIVESTOCK, and MARKD. We found statistically significant clusters of high CAI and high NDVI values, in the neighboring rural communities in southern districts of Burkina Faso, and clusters of low CAI and low NDVI values in the neighboring rural communities in the Sahel and Central North districts (Fig. 6a). However, in these districts and also in the East, we observed a considerable number of clusters of low CAI and low values of livestock in the neighboring rural communities (Fig. 6e), as well as clusters of high CAI and surrounding high values of livestock in the Center and Central Plateau districts. Similarly, there are significant clusters of high CAI and high rainfall (Fig. 6b). Significant clusters of high CAI and high PD in the southwest (Fig. 6d) can be observed. We also observed statistically significant clusters of low CAI and high MARKD, and high CAI and low MARKD in neighboring rural communities in the East and Central East districts (Fig. 6f).

We investigated the effect of different adaptive bandwidths (proceeding with proportions from 0.3 to 0.05) on local estimation in GWR. We observed that the variations in the stationary index for all predictors were larger for small bandwidths (proportions of 0.1 and 0.05). The stationary index became quite flat with increasing bandwidths (for greater than 0.1). At the smallest adaptive bandwidth (proportion of 0.05, i.e., on average 15 neighboring rural communities), we observed that, compared to the global model, the AIC value of GWR decreased from 410 to the highest minimum value of 340 and, the $R^2{}_a$ value increased from 0.24 to highest maximum value of 0.50. The ANOVA *F*-test suggests that GWR was a significant improvement ($p = 0.01$) over the global model. Moreover, we observed a decrease in Moran's I value of GWR residuals close to zero (−0.04).

The maps of local coefficients from the GWR models for NDVI (mean), RFE (amplitude 3), SLOPE, PD, LIVESTOCK, and MARKD variables are shown in (Fig. 7a–f). We observed high local variability of these coefficients in the study area. For example, Table 3 shows that a significant negative correlation exists between CAI and PD ($r = 0.116$, $p = 0.01$). Fig. 7(d) however shows that both negative and positive correlations occur in the study area. Stronger negative correlations show that a decrease in the population density may cause a higher increase in CAI in the North, Centre, and in the East of study area. While positive correlations are mainly located in the South and southwest of the study area. Similarly other spatially varying local coefficients show the spatial non-stationarity of the relationship between CAI and related stressor variables at 303 surveyed locations.

The GWR predicted CAI (Fig. 8) show less marginal rural communities in the southern half of the country as compared to in the eastern and northern regions. This indicates that the poverty remains pronounced in the North, South Central, Central Plateau, Boucle du Mouhaun, and East Central (Fig. 1), while the rural communities in the Center and in the Sahel regions become more poor. In these regions, the predicted CAI belonged to the high marginality range (i.e. CAI = 0.43–0.58). RS-based products (Fig. 2) revealed high agro-ecological stress in these regions. In Cascades and Haut Bassins, the predicted CAI fell within the low marginal range (i.e. CAI = 0.59–0.71). While both low and high marginal rural communities can be found in the Southwest, West Central, and in the East regions.

Table 4 compares the accuracy of the observed and the GWR predicted CAI. Compared to the histogram of the observed CAI (i.e. based on AGRISTAT data), GWR slightly overestimated the minimum values and underestimated the maximum values. For each of the Burkinabé regions, Table 5 presents a comparison between the average CPI computed from the predicted CAI and the average HCI obtained from 2009 national surveys. No significant difference is observed between the two indices. CPI was lower for the North region (21%) and higher for the Sahel (24%), Central (70%) regions.

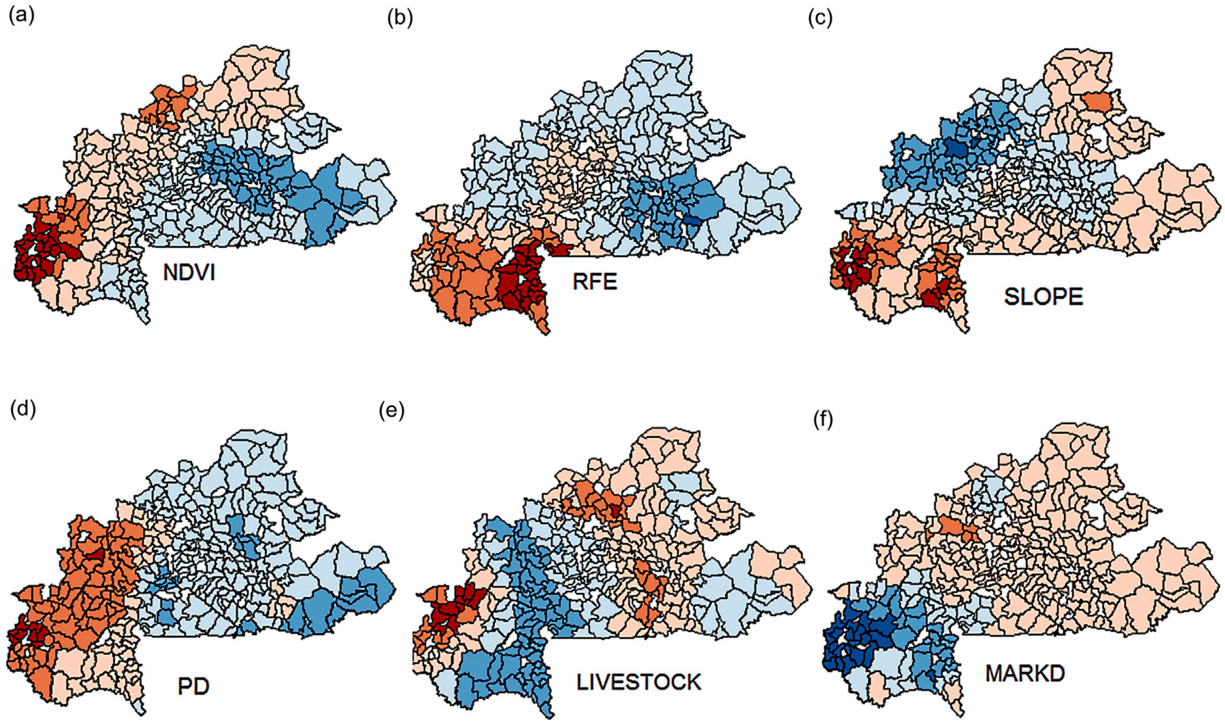

Fig. 7. Classification of the geographically weighted regression (GWR) coefficients for communal composite asset index (CAI) using proportion of rural communities (adaptive bandwidth = 0.05) – (a) the normalized difference vegetation index (NDVI), (b) rainfall estimates (RFE), (c) slope, (d) population density (PD), (e) poultry and small livestock (LIVESTOCK), and (f) market distance (MARKD). Light blue = Min; Dark brown = Max. Using six natural class breaks on the GWR coefficient values ranges in Table 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

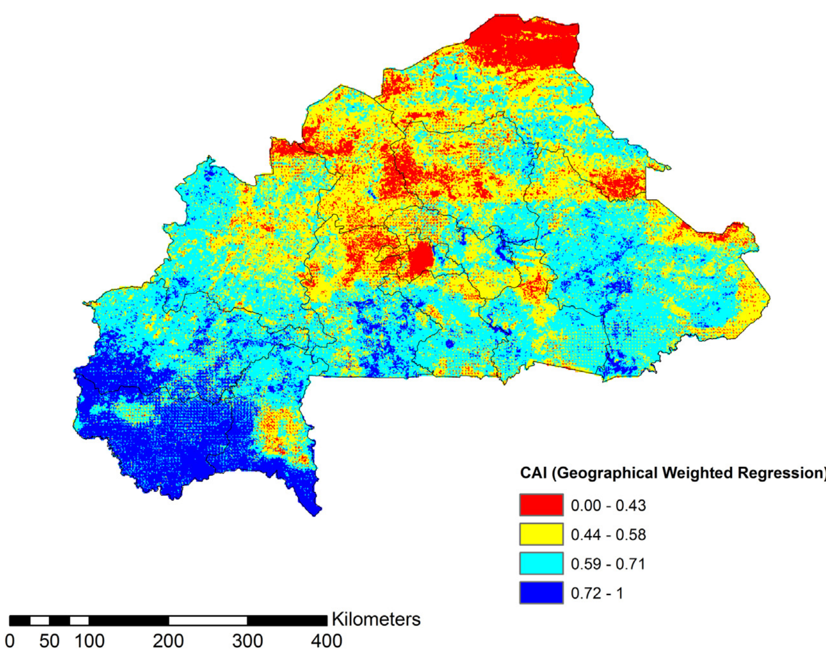

Fig. 8. Interpolated composite asset index (CAI) using geographically weighted regression (GWR).

Table 4
Histogram statistics, mean absolute errors (MAE), mean square errors (MSE), and root mean square error (RSME) to compare the differences between the original and the predicted composite asset index (CAI) using geographical weighted regression (GWR).

Model	*n*	Min[a]	1st *Q*[b]	Med[c]	3rd *Q*	Max[d]	Mean	MAE	MSE	RMSE
Observed	303	0.177	0.426	0.547	0.665	0.983	0.549	–	–	–
GWR	273,151	0.342	0.491	0.557	0.613	0.794	0.550	0.139	0.0283	0.168

[a] Minimum.
[b] Quartile.
[c] Median.
[d] Maximum.

Table 5
Comparisons of the average communal poverty index (CPI) with the head count index (HCI) in 13 regions of Burkina Faso.

Region	Average HCI (1998–2009)	HCI (2009)[a]	Mean CPI (CPI = (1 − CAI) × 100)[b]	
			Observed[c]	Predicted (GWR)
Boucle du Mouhoun	55.1	56	43	46.2
Cascades	37.1	37.3	37.9	33.1
Center	18.7	17.3	59.6	57.2
East Central	50.9	46.6	44.8	45.1
North Central	41.3	31.9	54.2	49.5
West Central	41.7	38.8	44.3	45.9
South Central	57.1	46.7	45.9	45.2
East	49.9	62.2	43.4	44.7
Hauts Bassins	38.2	46.8	40.3	39.7
North	65.8	68.1	46.2	52.2
Central Plateau	50.5	42.9	42.6	47.7
Sahel	38.5	36.6	55.9	51.9
Southwest	49.4	46.8	41.9	39.7

[a] HCI obtained from the 2009 national surveys of household living conditions.
[b] Regional means of CPI based on the communal composite asset index (CAI) predictions from geographical weighted regression (GWR).
[c] Regional means of CPI based on the CAI observed in the AGRISTAT data.

5. Discussion

To investigate rural welfare in Burkina Faso, an index, CAI, is composed from variables representing household assets in the 2009 AGRISTAT survey data. Weights are assigned to the correlated asset variables by using a sound statistical procedure, so that CAI reflects the contribution of each individual asset. Our results show that the CAI effectively characterizes the differing welfare levels of rural communities. The CAI observations at surveyed community locations are related to the collocated values of stressor variables. By exploring these relationships locally, the geographical weighted regression (GWR) is a more suitable and robust approach for retrieving a sufficiently varying measure of poverty and marginality of rural communities.

Well-justified variables are used to create the CAI so that it can provide a strong logical base for poverty mapping. For this we performed both an extensive review on poverty mapping in West Africa and an in-depth assessment of existing poverty patterns in the country's household survey data. We observed that poor households in rural Burkina Faso often have marginal food production (i.e. insufficient to meet their consumption requirements). This is also reflected in the AGRISTAT data where food insecure households consistently fail to attain an adequate cereal production for food consumption (AGRISTAT, 2010). To compose the CAI we, therefore, selected asset variables that are directly related to household food production and consumption. The factor analysis confirms our choices as the Chi-square significance ($p < 0.05$) suggests that the common factors can sufficiently explain the intercorrelations among the variables included in the analysis. This analysis also shows that the first factor of CAI has loadings on the household asset variables, including expected cereal production, cereal stocks, and number of animals owned. Obviously, these variables can be related to the levels of household food production in the study area. Also, the variance of second CAI factor is significantly (88%) explained by the asset variable on household food consumption.

The calculation of the CAI, in this study, requires a logarithmic transformation of the asset data, followed by a Min–Max transformation to the [0,1] interval. In this way we can arrive at a common measurement scale not affected by the units of each asset variable. To justify this, we explored several other methods as well. Those include ranking, standardizing the data towards values with zero mean and a standard deviation of one, and use of a categorical scale level. The Min–Max proves the most robust one in terms of taking into account the data properties and being closest to a normal distribution.

The CAI is related to various regional and global spatial datasets from a range of domains, including (i) RS-based products depicting agro-ecological stresses related to weather, soil and topography, (ii) maps of urban, rural and total population densities, and (iii) maps showing distance to markets and travel time maps indicating degree of geographic accessibility to urban cities of population size 20, 50, 100, and 250 thousands. Spatial variation of the CAI in rural communities is, however, mainly affected by the variables belonging to the agro-ecological domain. These variables indicate a strong environmental stress on the households' food production potential. Because of this stress, the rainfed cereal production is destined mainly for household consumption, with only 10–20% of the cereals brought to market (USAID, 2009). For the arid and semiarid regions in the North, a highly positive local relation between CAI and livestock (Fig. 6e) indicates that marginal communities tend to have more livestock to counter less favorable agro-ecological conditions.

The proposed CAI has strong local correlation with the stressors from RS-based products. Spatial prediction models incorporate local dependence into the process of prediction, for which GWR tends to calibrate local models on each surveyed location. The GWR technique has been widely used to investigate spatial nonstationary present in geographical relationships (Fotheringham et al., 2002). Local coefficient estimation in GWR largely depends on selecting an optimal kernel bandwidth (Gao et al., 2003; Leyk et al., 2012). Furthermore, the GWR technique is more sensitive to the effect of multicollinearity (Wheeler and Tiefelsdorf, 2005) than the OLS regression. A careful use of diagnostic statistics is, therefore, accomplished in this study to confirm reliable GWR experimentation. Both the diagnostic testing and the visual interpretation of local coefficient distributions in study area show significant spatial non-stationarity of the stressor variables.

The reason of positive GWR relationships between CAI and PD may be that a higher population density is usually related to more labor availability. Areas having a higher rate of arable land growth often face labor constraints (West et al., 2008). About 18% of the country's 46% arable land is concentrated in the West and South of the study area (USAID, 2009). Negative GWR relationships between CAI and population density may be attributed to a relatively high population growth as compared to increase in cultivation land per household, which often exerts greatest pressure on land nearby urban centers, and in the Central Plateau. The negative correlation of MARKD with CAI means that a decrease in the distance to market is associated with an increase in welfare. One possible explanation for this negative relationship is that distant locations are usually accompanied with a decline of community's ability to access food from markets. Particularly in livestock-dominant eastern and northern regions, a low cereal production level and being far from market together put a rural community at risk of getting high food prices (USAID, 2009).

Compared to the HCI in the Center, a high CPI average is observed in some rural communities nearby the urban areas. This indicates that some non-farm activities are contributing heavily to the communal income and employment. Slightly above-average CPI is observed in Sahel. It is a livestock dominant region because lack of favorable agro-ecological conditions often poses a low cereal production. Slightly below-average CPI value in the North region may be due to the fact that the welfare in CAI is evaluated in the view of households food production potential based on both the current cereal stocks and the expected cereal production. Whereas, HCI calculated from the national surveys indicates proportion of household whose current expenditure level is under the established poverty line (i.e. 1 USD adult^{-1} day^{-1}).

In addition to the link to agricultural and livestock production system, further experimentation with this approach to poverty extrapolation is needed. This should include the following: (i) evaluating welfare variables that represent non-farm activities, e.g. fishery, handicrafts, mining, particularly for communities residing near the urban areas or for considering rural employment during the dry season, (ii) other stresses to food productivity like limited access to inputs, credit, and land, and (iii) evaluating the effect of food utilization like limited access to adequate health services, potable water and sanitation.

We intend to use this study output in our ongoing research to spatialize the bio-economic farm model (BEFM) over large areas in West Africa. This BEFM focusses on Burkinabé subsistence rural communities and helps formulate sustainable farm policies, by effectively associating the production potential of their land parcels and their marginality status and food consumption requirement. The marginality assessment is necessary to further asses the communities capability of applying modern inputs like fertilizers, pest control, and crop varieties. Serving this input, the poverty and marginality maps will allow parameterizing the BEFM for all 7000 rural communities in Burkina Faso. Further extending this approach to the whole of West Africa will require a careful selection of asset variables to compose welfare index for rural communities in the entire region.

6. Conclusion

This study shows the performance of the composite asset index (CAI) for poverty mapping in Burkina Faso. The index replaces common indices, and is based on survey data. CAI is interpolated and mapped towards the entire country by using the RS-derived external covariates that represent agro-ecological stress.

The study shows that 58% of the variance of CAI is explained by the factor representing variables of food production and 42% is explained by the factor representing variables of food consumption. The composite asset index thus well represents the variation of welfare and marginality in terroir communities. This variation is significantly explained by the stressor variables of NDVI, rainfall, length of growing period, soil nutrients, and topography. Spatial dependency between CAI and the stressor variables is incorporated into a geographically weighted regression (GWR) model that is able to identify areas where poor agro-ecological conditions constrain terroir communities from attaining an adequate level of welfare.

We conclude that level of household food production and consumption is directly related to a welfare and poverty level in the Burkinabé terroir communities. Relationship between CAI and the stressor variables varies considerably between the terroir communities. The composite poverty index (CPI) based on the predicted CAI showed similar patterns as compared to the commonly applied head count Index. We thus conclude that agro-ecological marginality and poverty incidence are positively related in terroir areas of Burkina Faso.

Timely, cost-effective, and fine resolution poverty maps of CAI are generated targeting terroir areas. These maps can be applied for decision making related to food security and poverty. This study has thus highlighted the potential of the proposed method to identify causes of poverty that may help formulate better policies.

Appendix A. Parameter values to apply HANTS

The curve fitting procedure in each HANTS run was controlled by setting the following parameters:

1. Number of frequencies (NOF): 3, i.e., annual, semi-annual (6 months) and seasonal (3 months) frequencies.
2. Hi/Lo suppression flag (SF): low, i.e., the low values are rejected during curve fitting, because cloud contamination always corresponds to low or negative values. Particularly in the case of NDVI, cloud affected observations are remained even after applying the classical maximum value composting algorithm.
3. Fit error tolerance (FET): 0, i.e., curve fitting continued until all invalid values were removed.
4. Invalid data rejection threshold (IDRT): 1-254
5. Degree of overdeterminedness (DOD): 13, i.e., curve fitting was applied such that the 13 observational data points remain available in addition to the minimum data points.
6. Delta: 1 for the NDVI time series and 100 for the RFE time series.

For further details on these parameters see Roerink et al. (2000).

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