Targeting investments in roads, small-scale irrigation and rural electrification in Burkina Faso

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Program of Accompanying Research for Agricultural Innovation

MARCH 2020
research4agrinnovation.org

Published by:
Zentrum für Entwicklungsforschung (ZEF) | Center for Development Research
Genscherallee 3
D – 53113 Bonn, Germany
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Citation:
Combary, O., Maruyama, E., Scollard, P. and Xie, H. (2020). *Targeting investments in roads, small-scale irrigation and rural electrification in Burkina Faso.* Program of Accompanying Research for Agricultural Innovation (PARI), Center for Development Research (ZEF), University of Bonn, Bonn.

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Abstract

The agricultural sector plays a major role in the economic and social development of the population in Burkina Faso. However, essentially based on rainfed production, the low-productivity agriculture in the region is largely dependent on climatic hazards that repeatedly compromise their national food security. In this study, we develop a spatial and economic tool for strategic analysis and visioning to help understand where the best opportunities for rural infrastructure investments are in Burkina Faso. Our proposed approach utilizes stochastic frontier analysis to (i) identify areas of high agricultural potential with low accessibility to prioritize investments in road infrastructure according to a spatial model that estimates the minimum time taken to travel from any point in a country to the nearest market, and (ii) estimate average household gains in agricultural efficiency by comparing smallholders' performance under current conditions and under a scenario of improved access to small-scale irrigation and rural electrification. Our results for Burkina Faso show a clear north – south divide in terms of agricultural potential: low potential in the north of the country versus higher potential in the south. The estimated agricultural efficiency, which measures the degree to which a region succeeds in operating on its profit frontier, shows an east – west divide, with higher efficiency regions appearing more often in the western part of the country. Superimposing the market access measure on the attainable agricultural potential estimates brings into focus two regions as priority areas for investments in expanding and improving the road network: the Est and Sud-Ouest regions that combine medium to high access times to markets with medium to high attainable agricultural potential. Finally, our analysis shows that the biggest gains in revenues from small-scale irrigation and rural electrification investments occur in the Sud-Ouest, Boucle du Mouhoun (Bale province), Centre-Est and Est regions, while lack of access to water sources limits the potential for small-scale irrigation and the benefits from electrification in the Sahel region in the north.

Keywords*:* Production Efficiency Measures, Agricultural Policy, Rural Development, Economic Geography

JEL codes: D24, O13, O18, Q18, R11, R12

Acknowledgements

The study was supported by the “Program of Accompanying Research for Agricultural Innovation” (PARI), which is funded by the German Federal Ministry of Economic Cooperation and Development (BMZ).

1. Introduction

Burkina Faso is a landlocked, low-income country in Sub-Saharan Africa (SSA) with high demographic growth as well as high levels of poverty and gender inequity. With a Gross National Income per capita of US$790 in 2019. The agricultural sector plays a major role in the economic and social development of the population in Burkina Faso. Agriculture generates more than 30 percent of the GDP and is the main occupation of more than 80 percent of the country's working population, with over 70 percent of its agricultural production provided by small-scale rural producers who practice subsistence agriculture (Ministère de l'Economie et des Finance, 2018). Burkina Faso is one of the poorest countries in the world and depends strongly on food imports to meet its domestic food demand. In 2019, the poverty rate was 37 percent (using the international poverty line) and was expected to rise to over 39 percent in 2020 because of the economic crisis induced by the Covid-19 pandemic. Poverty is overwhelmingly concentrated in rural areas, which are home to 90 percent of poor households, and is largely attributed to under-employment, limited social inclusion, low agricultural productivity and poor access to electricity.

Despite its prominent role in the country's economy, the agriculture sector performs poorly in terms of crop and livestock productivity growth (USAID Burkina Faso, 2015). Therefore poverty reduction in Burkina Faso requires agricultural improvements for economic growth. However, an analysis of the dynamics of the agricultural sector in Burkina Faso reveals that its growth is subject to structural deficiencies. Essentially based on rainfed production, this low-productivity agriculture is largely dependent on climatic hazards that repeatedly compromise the national food security. Among the bottlenecks that hinder the development of the agricultural sector, the World Bank identified the infrastructure deficit and lack of policy coherence as major obstacles underlying the country's poor performance (World Bank, 2007). For these reasons, roads, irrigation and electrification projects have been frequently favoured by governments and donors looking to invest in infrastructure to accelerate economic growth and development in rural areas.

We hypothesize that for investments in roads, irrigation and electrification to be effective for poverty alleviation, it is necessary that they lead to farm-level increases in productivity and are translated into higher incomes and better livelihoods for rural households. Therefore, we develop a spatial and economic tool for strategic analysis and visioning to help understand where the best opportunities for investments in roads, small-scale irrigation and rural electrification are in Burkina Faso. The paper is organized as follows. After the first section devoted to the introduction, Section 2 describes the state and role of the road, irrigation and electricity infrastructures in the country. Section 3 describes the methodology and the data source. In Section 4 the findings are presented followed by the conclusion in Section 5.

2. Context of the study

Infrastructure investment is crucial for Burkina Faso's development due to its geographic position and climatic condition. For the transport, Burkina Faso relies on its road network to overcome its landlocked condition which imposes a mark-up on import and export costs, but also to benefit from its central position as a natural transit hub for West Africa (World Bank, 2007). Consequently, the country has developed four corridors to access international ports, (the Abidjan Road and Railway Corridor, the Lome Corridor, the Tema Corridor and the Cotonou Corridor) and has made maintaining regional roads in good condition a top strategic priority. However, while international and national connectivity is adequate, accessibility is poor beyond the trunk network, particularly in rural areas with only 25 percent of the rural population living within two kilometres of an all-weather road (Gwilliam, et al., 2008). The spatial distribution of Burkina Faso's population, with a high concentration in the middle of the country and much more dispersed elsewhere, makes it particularly challenging to increase accessibility in rural areas by improving the quality of the existing rural network, in particular in the northeast areas of the country (Briceño-Garmendia & Domínguez-Torres, 2011).

In addition, like in most Sahelian countries, there is a need to invest in irrigation in Burkina to reduce the dependence of the agricultural sector on rainfall. Annual rainfall averages around 750 mm; the northern Sahelian area typically receive less than 600 millimeters while the southern Sudanian region receives up to 1,200 mm. However, rainfall has been gradually decreasing since the severe droughts of the 1970s (Sally et al., 2011). Inadequate rainfall necessitates irrigation for successful agriculture, yet infrastructure is poor and farmers' access to irrigated water is low (FAPDA, 2014). Despite a potential of 233,500 hectares of irrigable land with total water control and 500,000 hectares of easily manageable lowlands, irrigated agriculture remains negligible, with less than one percent of cultivated land in Burkina Faso being equipped for irrigation (Mathematica Policy Research, 2018). Moreover, although total irrigated land doubled between 2004 and 2019, representing an average annual growth rate of seven percent, this rate of irrigation expansion is relatively slow given the initial low level of irrigated areas and the need for rapid growth of the agricultural sector. Crucially, the average annual growth rate decreased from ten percent in 2004-2013 to four percent in 2013-2019.

Finally, the situation of the energy sector in Burkina Faso requires investment in the sector to meet the increasing demand in the country. The price of electricity is one of the highest in the region, and the access rate is estimated at only 20 percent with a large gap between rural and urban areas (1.5 percent in rural areas, 58 percent in urban areas; Power Africa, 2020). In addition, Grid-connected electricity users suffer through both load shedding and poor quality of service. Total installed generation capacity is estimated at 355 Megawatt (MW). Burkina Faso also relies on electricity import from Côte d'Ivoire and Ghana. The network is interconnected with Côte d'Ivoire through a 225 kilovolt (kV) transmission line supplying 70 MW and with Ghana through a 330kV transmission line commissioned mid-2018 that currently supplies an additional 40 MW. It was estimated that imports represented 37 percent of electricity supply in 2017, a share expected to grow significantly with imports from Ghana. Electricity supply is just enough to precariously meet the demand which increases by 10 percent per year. The capacity deficit to meet peak loads in 2019 is estimated at 40 MW (World Bank, 2019).

3. Methodology and data source

3.1 Empirical strategy

This study aims at assessing the link between agriculture-driven growth, poverty reduction, road infrastructure, small-scale irrigation and rural electrification investments. Therefore, these assessments include the economic components of the environment in which smallholders operate, such as market prices and the degree of access to those markets. For investments in rural infrastructure to be effective for poverty alleviation, they need to lead to farm-level increases in productivity and be translated into higher incomes and better livelihoods for rural households.

Our proposed approach utilizes a stochastic frontier analysis (SFA) to (i) identify areas of high agricultural potential with low accessibility to prioritize investments in road infrastructure according to a spatial model that estimates the minimum time taken to travel from any point in a country to the nearest market, and (ii) estimate average household gains in agricultural efficiency by comparing smallholders' performance under current conditions and under scenarios of improved access to small-scale irrigation and rural electrification. While similar, the methodologies for small-scale irrigation and electrification differ slightly from each other due to the intrinsic differences in how these services are provided. In the case of electricity, once the provider has expanded the grid close enough for users to connect to it, consumption is limited only by the cost of the service bill. For small-scale irrigation, while farmers need to invest in equipment such as motor or solar pumps, and cover some running costs (fuel, maintenance, etc.), biophysical factors such as the availability of adequate water sources (surface or groundwater) and the topography (slope) of the land can be insurmountable barriers regardless of the availability of funds. Hence, for the small-scale irrigation SFA estimation it is crucial to include the impact of the biophysical constraints on agricultural potential, while for the electrification SFA estimation, it is essential to make an adequate prediction of electricity consumption for currently unconnected households or regions.

The methodology for the small-scale irrigation analysis is illustrated in Figure 1. We use GIS measures for access to water sources (surface and groundwater) and slope, and the distance to agricultural markets (purple box) to capture the biophysical and economic constraints to small-scale irrigation and its impact on agricultural potential and efficiency through the SFA estimation (green box). We then simulate the impact of increasing access to small-scale irrigation, within the biophysical constraints established by the GIS variables on smallholder profits across the country (red box).

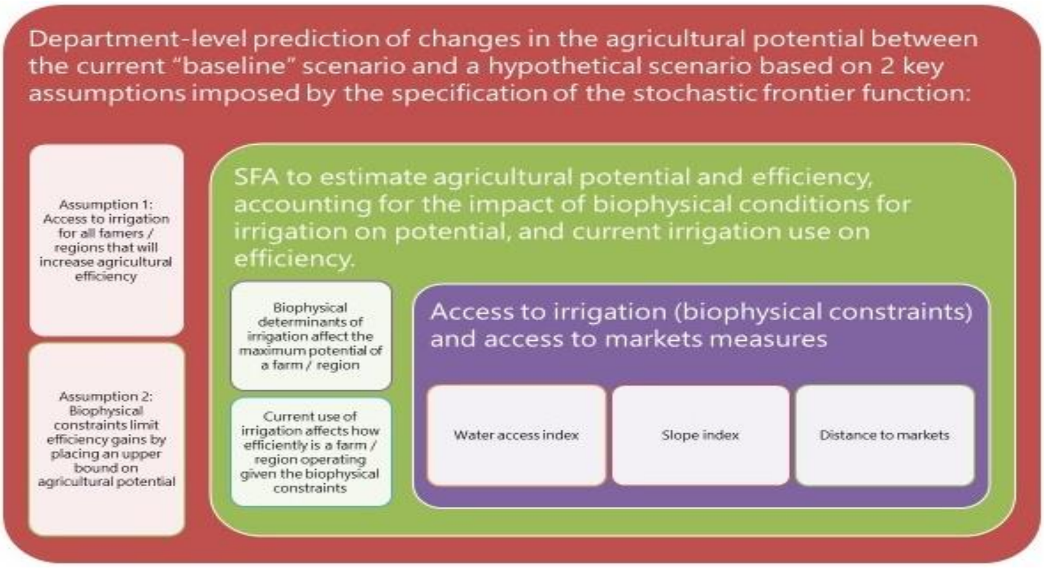


Figure 1. Methodological approach for small-scale irrigation analysis

Source: Own elaboration

The methodological approach for the electrification analysis is illustrated in Figure 2. The first step (in the yellow box) involves using a Heckman selection model (Heckman, 1976) to predict what would be the consumption of electricity for unconnected rural households under universal access. In the second step we estimate agricultural potential and efficiency estimates for smallholders using SFA under the assumption that electricity helps reduce the farms' efficiency gap. This allows us to compare estimated efficiency levels under current conditions and under universal access (using the predicted electricity consumption from the first step) and calculate what are the agricultural revenue gains from electrification. In the third step we extrapolate these results for the whole country and combine them with GIS information on the status of Burkina Faso's electrical grid and connectivity.

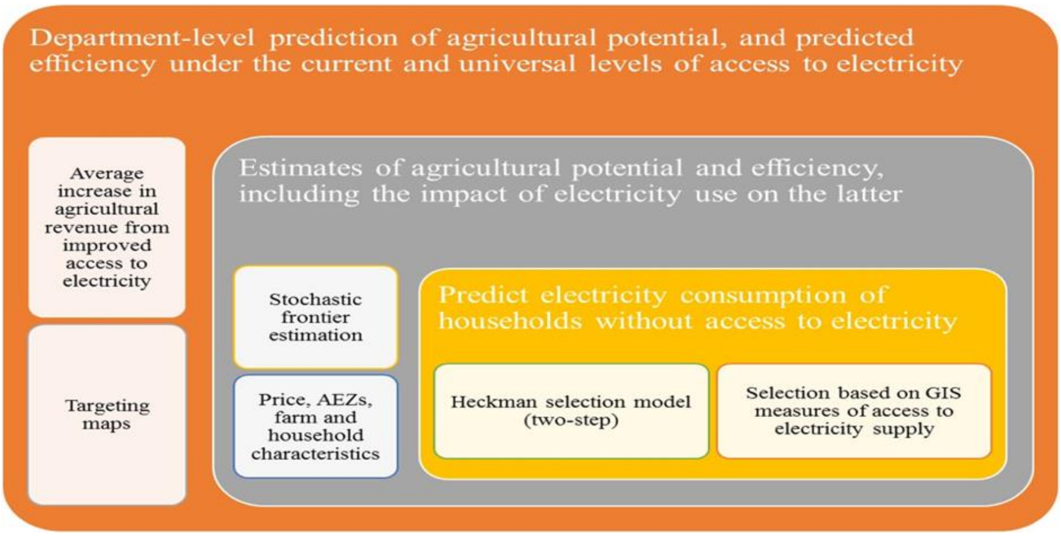


Figure 2. Methodological approach for electrification analysis

Source: Own elaboration

These approaches allow us to identify areas where improved access to markets could yield high returns for smallholders and compare estimated efficiency levels under current conditions and hypothetical scenarios of improved access to small-scale irrigation and electricity to assess the agricultural revenue gains linked to each case. Finally, we extrapolate these results for the whole country and combine them with GIS information on small-scale irrigation suitability, the countries' electrical grid and connectivity rates. Our analytical results and maps highlight the spatial heterogeneity in opportunities and priorities for roads, small-scale irrigation and electrification investments in Burkina Faso.

A more detailed description of the methodology is provided in the Annex.

3.2 Data source

The 2014 Enquete Multisectorielle Continue (EMC) is representative nationally, regionally and of urban and rural areas. Households were selected using a two-stage stratified sampling procedure. In the first stage, 905 enumeration areas were drawn with a probability proportional to the population. In the second stage, 12 households were selected with equal probability from each enumeration area. The survey was conducted in four rounds with the first round beginning in October 2013 and the final round finishing in October 2014. The agricultural module was only conducted once around the time of the final round of data collection while the other household characteristics included in our estimation were collected in all four rounds. Therefore, whenever a measure exists in more than one round, we include the value from the fourth round of data collection. If a measure is missing from the fourth round, then we fill in the value using the most recent round in which the value is available.

4. Results and Discussions

4.1 Descriptive Analysis

Statistics for the full EMC are provided in Table 1. Unfortunately, the EMC does not include detailed information on input use and prices, so instead of a farm profit frontier we estimate a farm revenue frontier. We also restrict the sample to households that have crop revenue equal to or greater than the price of one kilogram of peanuts. Our resulting sample size is 1,538 households.

Table 1. Burkina Faso EMC full sample: Summary statistics

	Mean	**Std. Dev.**
Prices		
Sorghum	125.59	12.89
Maize	93.16	21.05
Cowpea	191.21	22.33
Sesame	438.63	100.64
Cotton	225.03	0.83
Groundnuts	156.75	40.84
Household Characteristics		
Household size	7.16	4.88
Female head (%)	13.98	34.68
Maximum schooling (years)	3.81	4.75
Crop Revenue (XOF)	21,350.48	302,653.31
Land (ha.)	3.24	9.32
Farm asset value (XOF)	210,994.61	1,282,340.38
Manual Pump ownership (%)	3.52	18.43
Observations	10,800	

Source: Own elaboration

Summary statistics for this sample are presented in Table 2. Comparing to the full sample summary statistics, the households in the estimation sample look similar in terms of demographic and socioeconomic characteristics: household size, proportion of female headed households, and maximum years of schooling in the household. As would be expected, our estimation sample has a larger mean crop revenue, more land, higher value of farm assets, and is more likely to own a manual pump.

Table 2. Burkina Faso EMC SFA estimation sample: Summary statistics

	Mean	Std. Dev.
Prices:		
Sorghum	126.25	12.17
Maize	95.59	20.52
Cowpea	196.33	27.90
Sesame	448.57	130.40
Cotton	225.11	1.68
Groundnuts	159.19	44.42
Household Characteristics:		
Household size	8.30	5.06
Female head (%)	10.21	30.29
Maximum schooling (years)	2.38	3.45
Crop Revenue (XOF)	149,854.03	790,131.25
Land (ha.)	5.50	9.79
Farm asset value (XOF)	436,594.84	3,151,395.00
Manual Pump ownership (%)	8.97	28.59
Geospatial Variables:		
Accessibility (hours)	3.11	1.22
Slope Index	94.16	5.73
Water Access Index	44.81	6.12
Land Use (% of area):		
Water	0.03	
Shrublands	2.53	
Savannas and Urban	18.01	
Grasslands and Barren	24.10	
Croplands	2.94	
Other	52.40	
Observations	1,538	

Source: Own elaboration

4.2 Agricultural potential and efficiency

Results for the maximum likelihood estimation of the Heckman selection model are shown in Table 3. We assume electricity consumption (measured by the reported household's electricity expenditure) is a function of some basic household characteristics (household head's education, age and gender, household size and farm size), whereas the likelihood that a household has access to electricity (i.e. reports being connected to the grid) is a function of the grid infrastructure measured by the distance to electrified localities. As mentioned earlier, the lack of georeferenced locations for the EMC households reduces the precision of these estimates, but in terms of the point estimates, we observe, as expected, that living at a closer distance to an electrified locality positively affects the likelihood of having access to electricity.

Table 3. Access to and consumption of electricity (Heckman selection model)

Observations	1,538
Selected	64
Non-selected	1,474
Chi-square	1.95

Electricity Expenditure (XOF)	*Coeff.*	*Std. Error*
Head Education		
None (literate)	6,649.49	8,144.85
Primary	1,392.02	16,059.34
Secondary (1st cycle)	-4,499.45	15,952.29
Head Age	77.11	156.20
Head Female	-673.70	7,441.18
Household Size	139.70	802.22
Land	88.84	318.73
Constant	57,695.87	89,834.09
Connected		
Distance to Electrified Localitie	$-2.0\text{x}10^{-5}$	$1.9\text{x}10^{-5}$
Head Education		
None (literate)	-0.070	0.193
Primary	0.466	0.166***
Secondary (1st cycle)	0.387	0.307
Head age	0.001	0.004
Head Female	0.059	0.204
Household Size	0.018	0.012
Land	-0.005	0.008
Constant	-1.794	0.302***

Source: Own elaboration

Table 4 shows the SFA estimation with the inclusion of the irrigation and electricity measures. As mentioned above, the dependent variable is the log of farm revenues rather than profits because the EMC does not include detailed information on input use and prices. The deterministic portion of the revenue frontier is a function of output prices, AEZs (*land use* variables), and the small-scale irrigation suitability measures. The factors influencing (the variance of) the non-negative component of the error term associated with farm efficiency are electricity consumption, market accessibility, physical capital (land, assets, non-farm income), human capital (household size, household head characteristics), and an indicator for whether the farm owns a manual pump to proxy for current use of irrigation. The estimated coefficients from the regression in this table are used to predict regional level agricultural potential (capped by the level of suitability for small-scale irrigation) and efficiency (limited by the actual use of irrigation and electricity). Hence, for households without irrigation or electricity, the SFA estimation allows us to assess and map how much of the performance loss (in terms of farm profits) is due to the limited agricultural potential of the farm coming from the lack of access to water for small-scale irrigation, or from the efficiency loss due to the lack of investments to tap onto the existing water resources or connect to the electricity grid. Or, in other terms, we identify how much more profitable agriculture could be in a region by investing in small-scale irrigation and rural electrification projects that would allow local farmers to benefit from their untapped potential.

Both the water access index in the deterministic portion of the frontier function and the pump ownership indicator in the error term have the right sign but the point estimate is not significant. This, in part, could be caused by the fact that the EMC households are not georeferenced, so they are matched to province level averages of the GIS variables which results in a loss of precision. Also, pump ownership could be a weak proxy for irrigation use. The slope index is significant but has the incorrect sign, but given the little variation in the index this is not a big concern.

The negative sign on the electricity expenditure variable indicates that an increase in electricity consumption is associated with a reduction in technical inefficiency. The estimated coefficients from the regression in this table are used to predict regional level agricultural potential and efficiency. When combined with the predicted electricity consumption for unconnected households obtained from the Heckman selection model estimation, the results give us the potential and efficiency estimates for the universal access scenario.

Table 4. Burkina Faso: Electrification SFA estimation

ln(Crop Revenue)	Coeff.	Std. Error
Crop Prices		
Sorghum	2.878	0.411***
Maize	0.122	0.277
Cowpea	-1.668	0.502***
Sesame	0.671	0.147***
Land Use		
Shrublands	-8.499	1.461***
Savannas and Urban	-1.196	0.484**
Grasslands and Barren	-1.763	0.240***
Croplands	-2.241	2.817
Irrigation		
Water access index	0.001	0.009
Slope index	-0.059	0.017***
Constant	12.484	1.783***
$ln\sigma_v$		
Constant	0.606	0.046***
$ln\sigma_u^2$		
log electric bill	-0.287	0.170*
Manual pump ownership	-0.121	0.897
Market accessibility	-0.139	0.117
Land (ha)	-0.307	0.095***
log asset expenses	-0.323	0.053***
Household size	-0.072	0.037*
Head female	0.156	0.194
Head Education		
None (literate)	-0.224	0.536
Primary	0.323	0.183*
Secondary (1st cycle)	0.325	0.306
Secondary (2nd cycle)	0.917	0.847
Secondary (tech/prof)	-1.897	0.949**
Tertiary	0.080	0.178
Constant	2.999	0.400***
σ_v	1.354	0.031
N		1,538

Source: Own elaboration

Figure 3 shows the estimated agricultural potential for Burkina Faso, where agricultural potential is defined as the maximum possible revenue[1] that a farmer can gain from crop production if operating at maximum efficiency. The map shows a clear north – south divide: the low agricultural potential in the north of the country results from unfavourable conditions for agriculture with the predominance of shrubs, savannah and steppe, characterized by rocky soils, and a short-wet season that produces an average of 300 – 400 mm of rain per year. In contrast, the south received more than 750 mm of rain in 2013 (Figure 4).

[1] For this study, revenue is defined as total revenues from crop and byproduct sales plus the value of own consumption

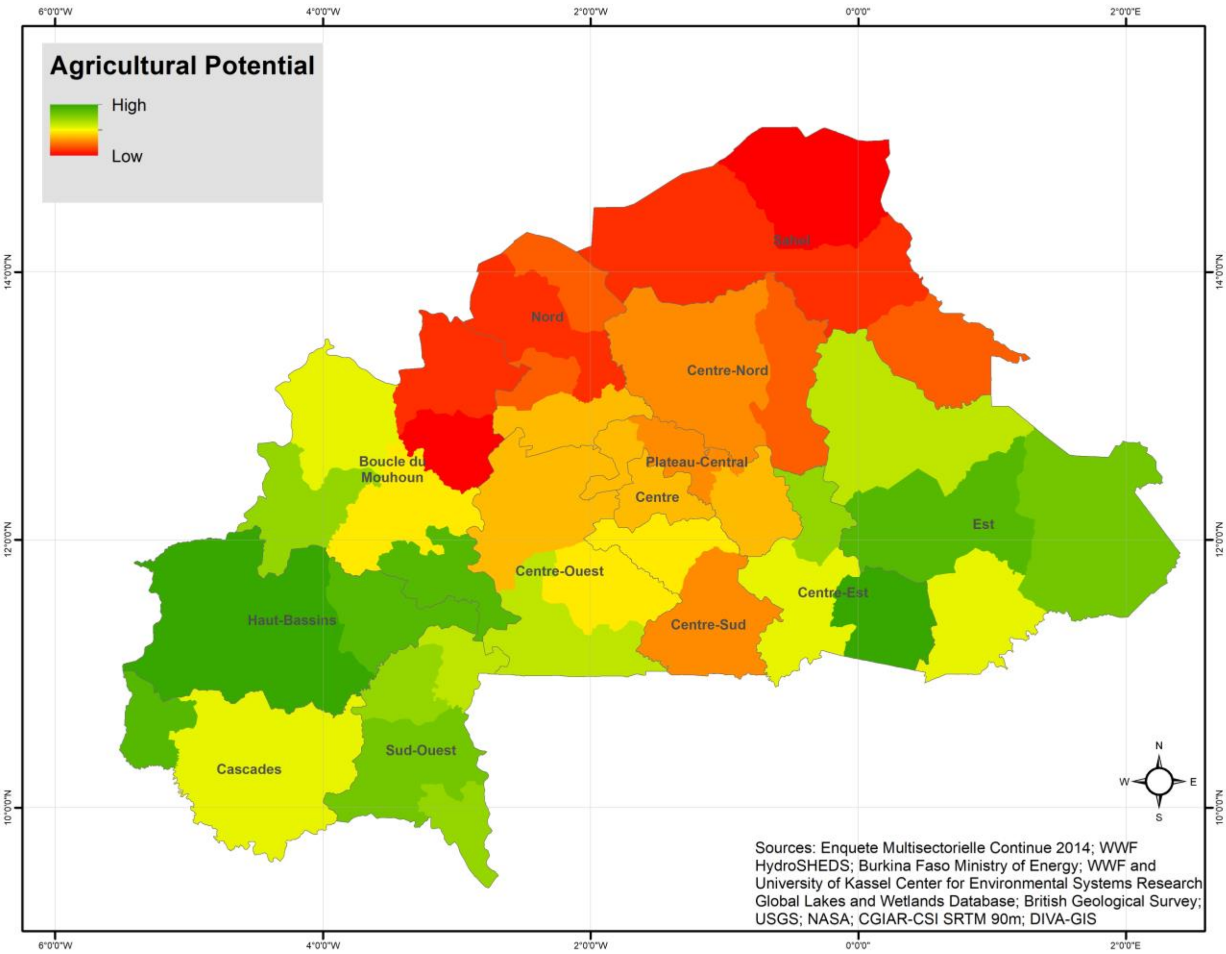


Figure 3. Burkina Faso: Agricultural potential

The estimated agricultural efficiency in Figure 5, which measures the degree to which the potential in Figure 3 has or has not been attained, shows an east – west divide, with higher efficiency regions appearing more often in the western side of the country. Combining potential and efficiency into a single map by estimating the attainable agricultural potential (Figure 6) helps to illustrate the existing potential yet to be attained in each region (i.e. the size of the potential or frontier gap). The combination of high agricultural potential in the south and high agricultural efficiency in the west is also consistent with the production patterns of major crops such as maize and rice (Figure 7 and Figure 8).

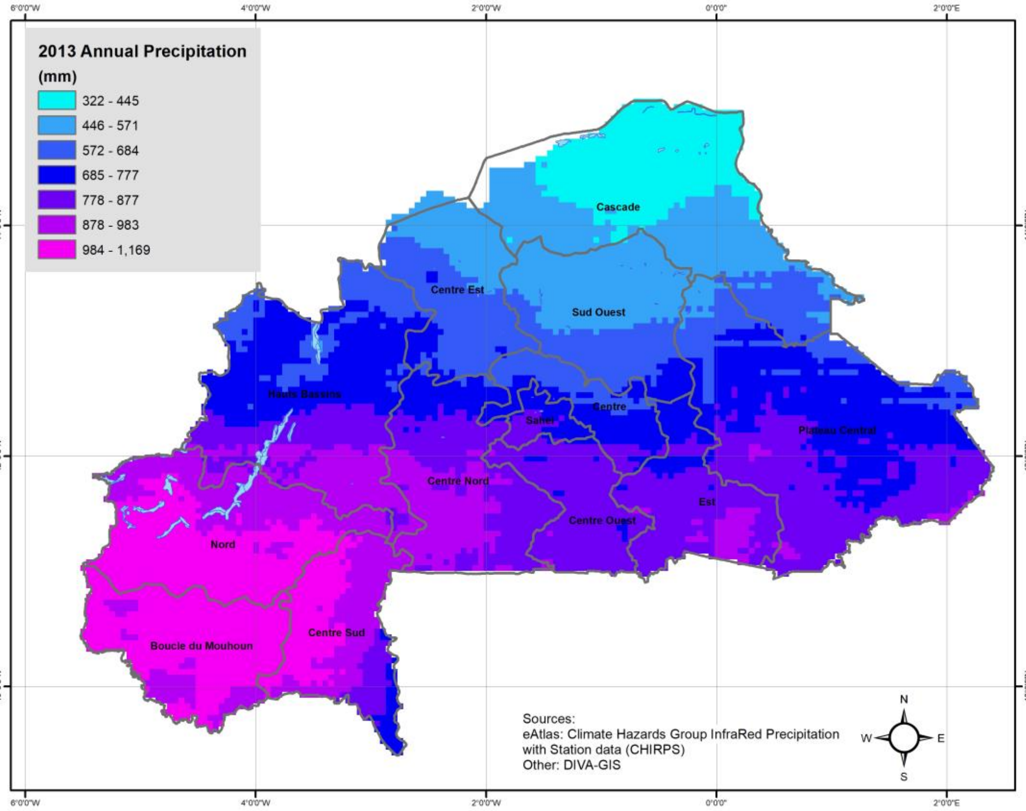


Figure 4. Burkina Faso: Annual precipitation (mm), 2013

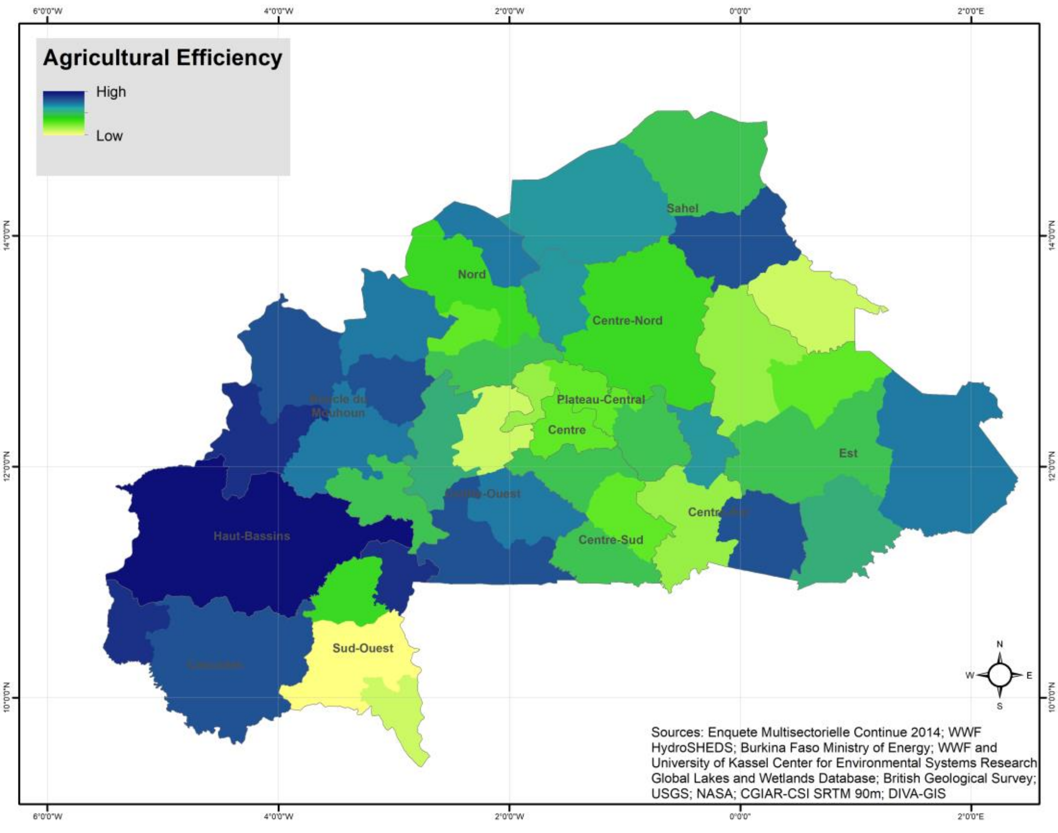


Figure 5. Burkina Faso: Agricultural efficiency

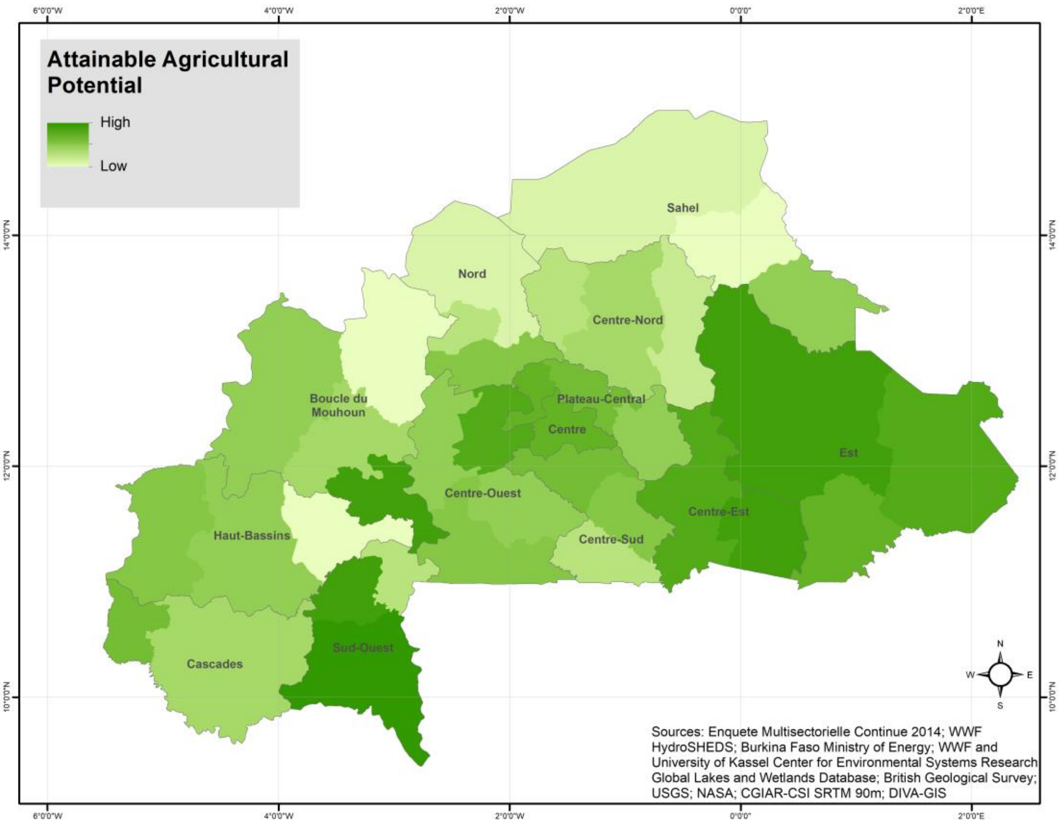


Figure 6. Burkina Faso: Attainable agricultural potential

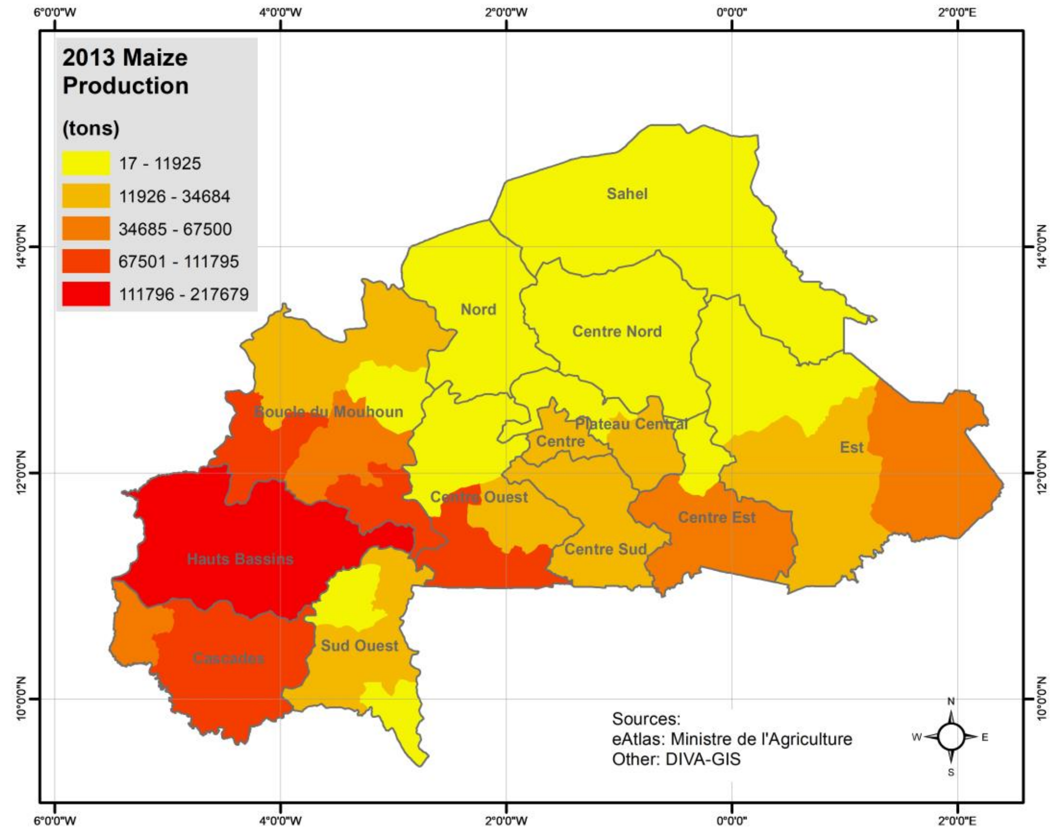


Figure 7. Burkina Faso: Maize production (tons), 2013

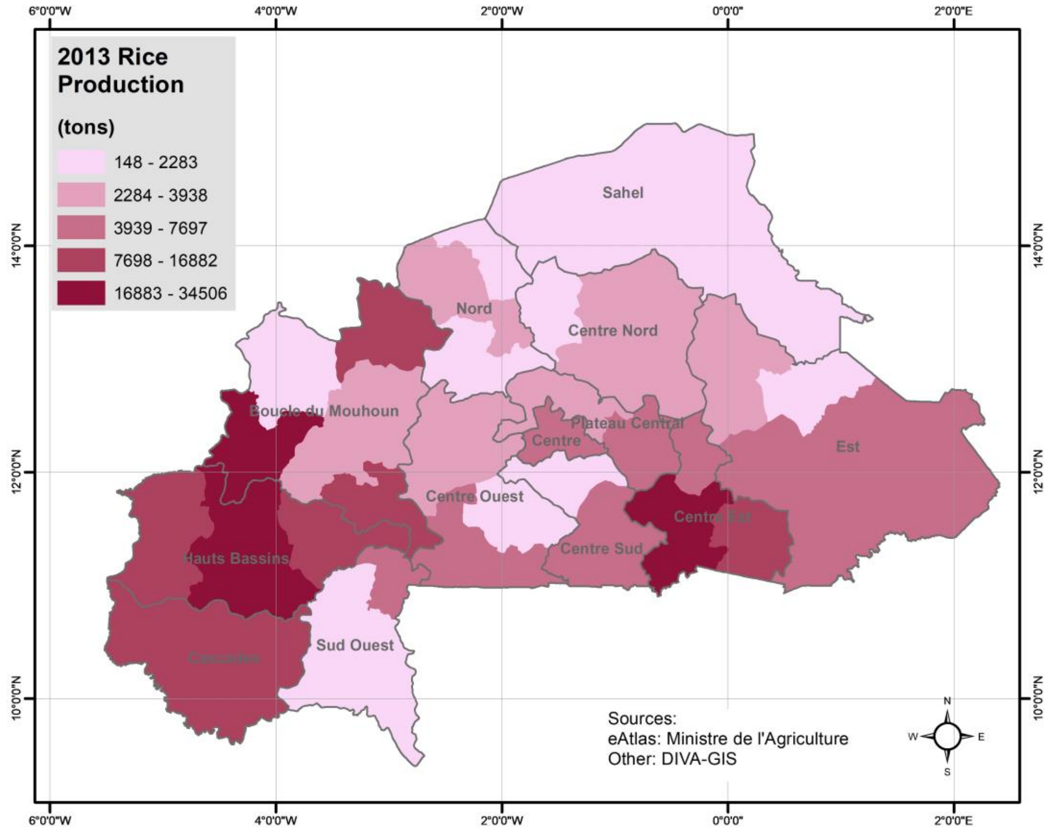


Figure 8. Burkina Faso: Rice production (tons), 2013

4.3 Accessibility and road infrastructure

One of the factors influencing efficiency is the degree of market accessibility each region has. For this purpose, we estimated the accessibility model (Figure 9) to determine the time costs of accessing the closest market, where *market* is defined as towns or cities with more than 25,000 inhabitants that can generate significant levels of demand for those products.

The map in Figure 10 shows the spatial patterns that result from superimposing the market access measure in Figure 9 with the attainable agricultural potential in Figure 6. The map can help us visualize poorly connected areas in the country with considerable growth potential from efficiency gains in agriculture. The two regions that come into focus as a priority for investments in expanding and improving the road network are the areas in red in the Est region and the areas in orange in the Sud-Ouest region that combine medium to high access times to markets with medium to high attainable agricultural potential.

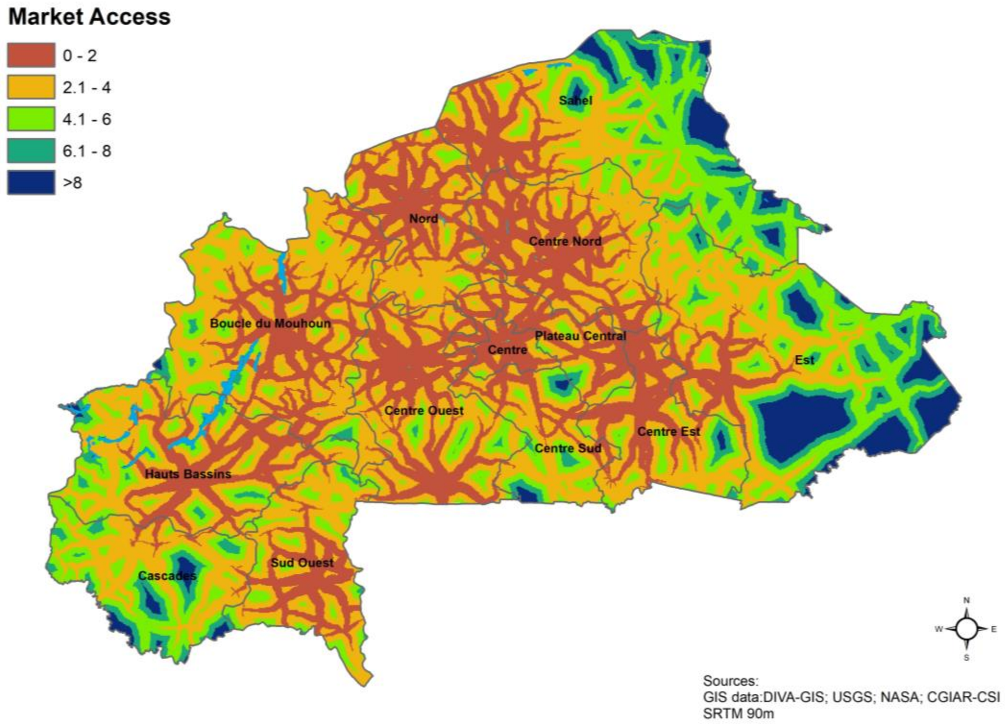


Figure 9. Burkina Faso: Accessibility to cities with more than 25,000 inhabs.

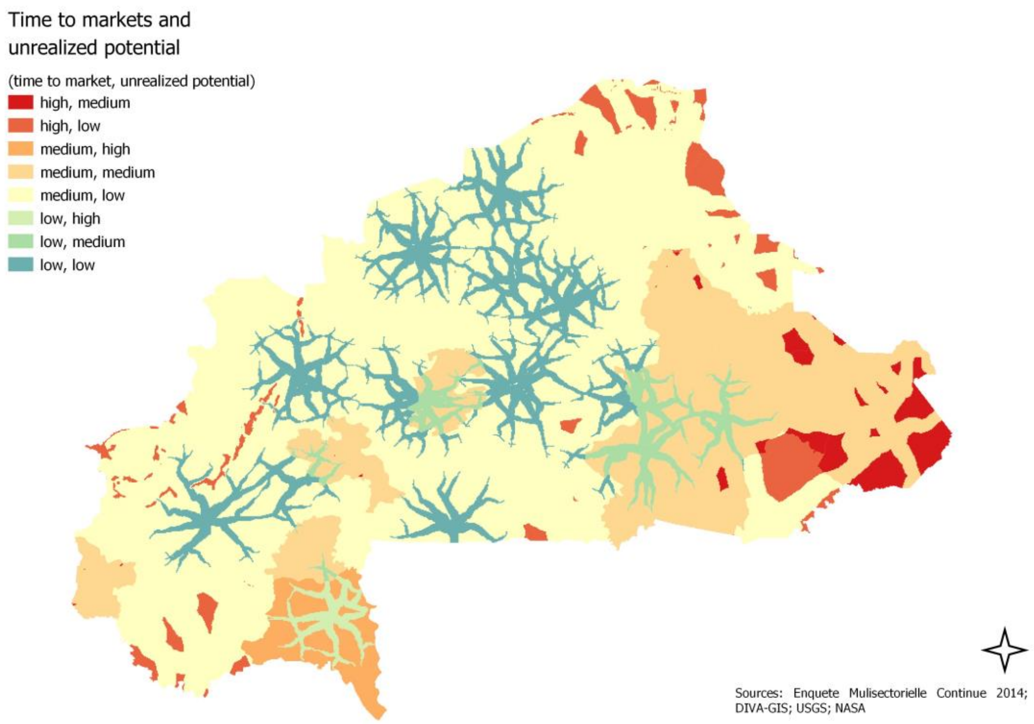


Figure 10. Burkina Faso: Attainable agricultural potential and time to markets

4.4 Profit gains from small-scale irrigation and rural electrification investments

Figure 11 and Figure 12 show the magnitude of the estimated revenue gains from investments in small-scale irrigation and rural electrification, respectively. This is the expected increase in profits that would result from moving farmers in each sample from their current irrigation adoption status to full adoption, given the constraints to their overall potential imposed by biophysical factors (access to water sources and slope) in the case of irrigation. Given that the biggest impact electrification can have on crop revenues in a setting with very low access to irrigation is by expanding the use of electric water pumps, it is not surprising that both maps are very similar. The biggest gains in revenues from small-scale irrigation and rural electrification investments occur in the Sud-Ouest, Boucle du Mouhoun (Bale province), Centre-Est, and Est regions, while lack of access to water sources limits the potential for small-scale irrigation and the benefits from electrification in the Sahel region in the north.

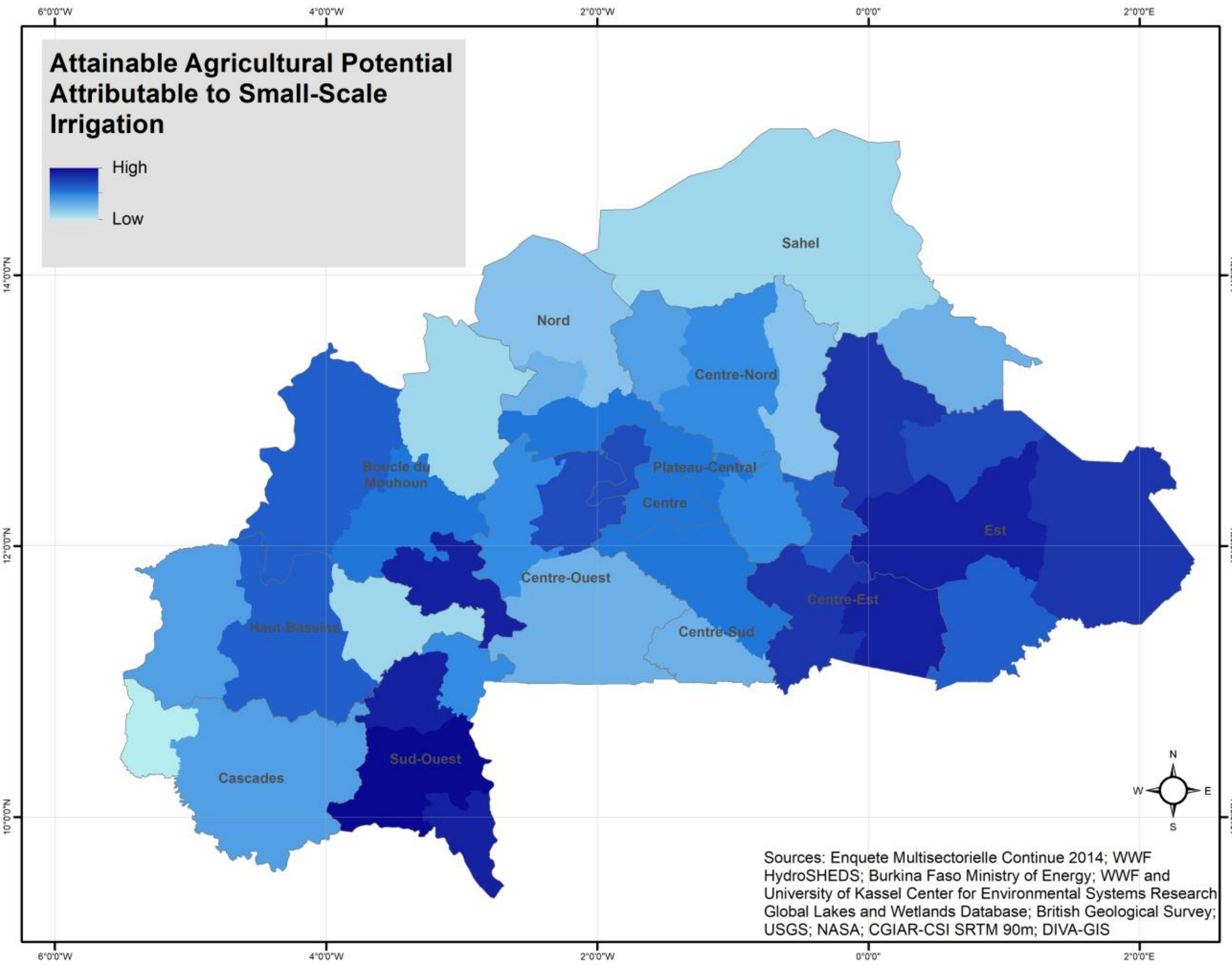


Figure 11. Burkina Faso: Revenue gains from irrigation

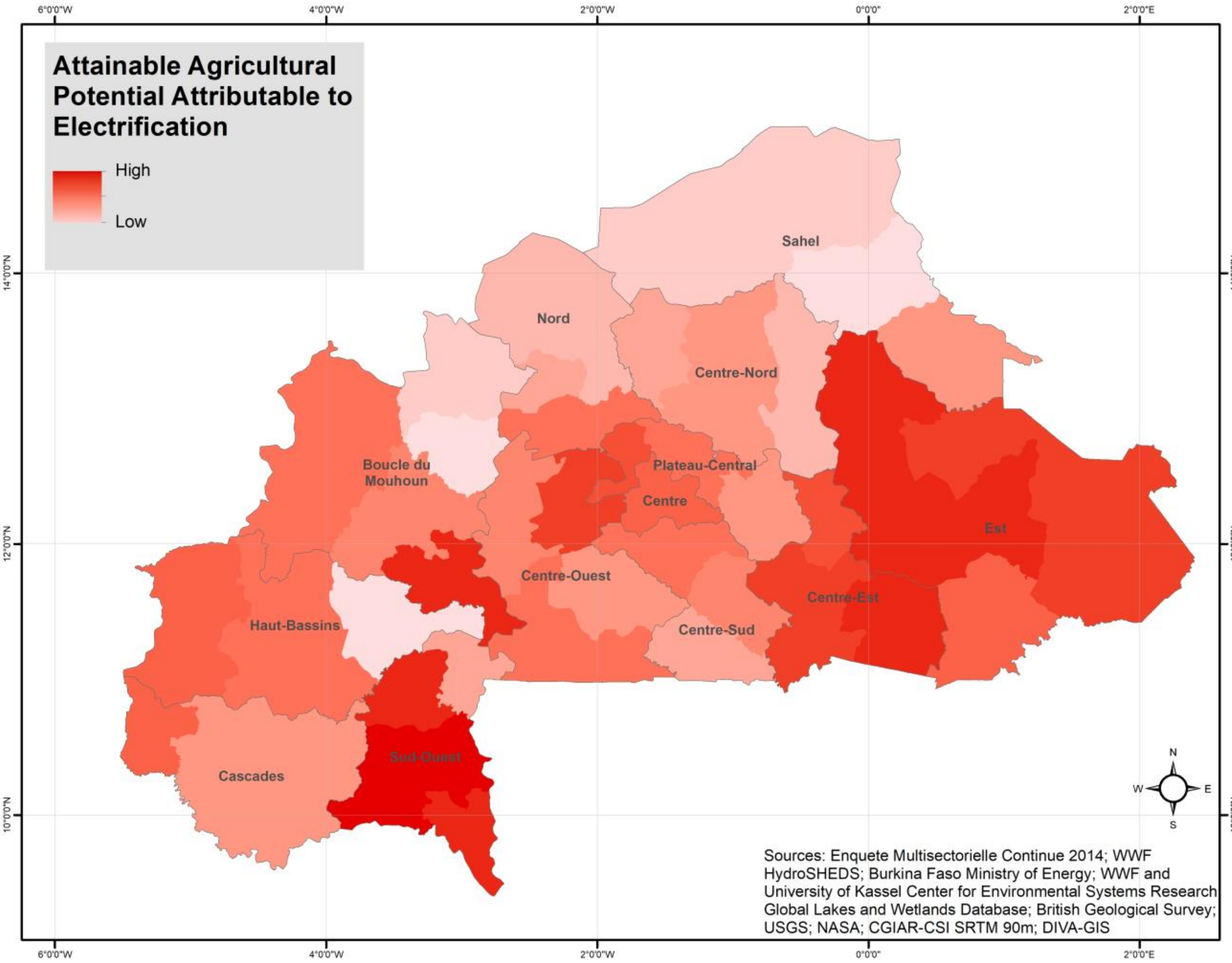


Figure 12. Burkina Faso: Revenue gains from electrification

4.5 Poverty and food security

In this section we discuss briefly how our analysis is complemented by considerations about the spatial distribution of poverty and nutrition outcomes. Figure 13 shows the province-level poverty map for Burkina Faso based on household data from the 2009 *Enquête Intégrale sur les Conditions de Vie des Ménages* (UNDP, 2014). The East is the region with the highest incidence of poverty (57.4 percent) and includes the two poorest provinces in the country (Tapoa, 61.4 percent, and Kompienga, 59.4 percent). However, all regions in Burkina Faso include at least one province with a poverty rate of 50 percent or higher, except for the Centre and Hauts-Bassins regions due to the relatively better living conditions in Ouagadougou and Bobo-Dioulasso, respectively.

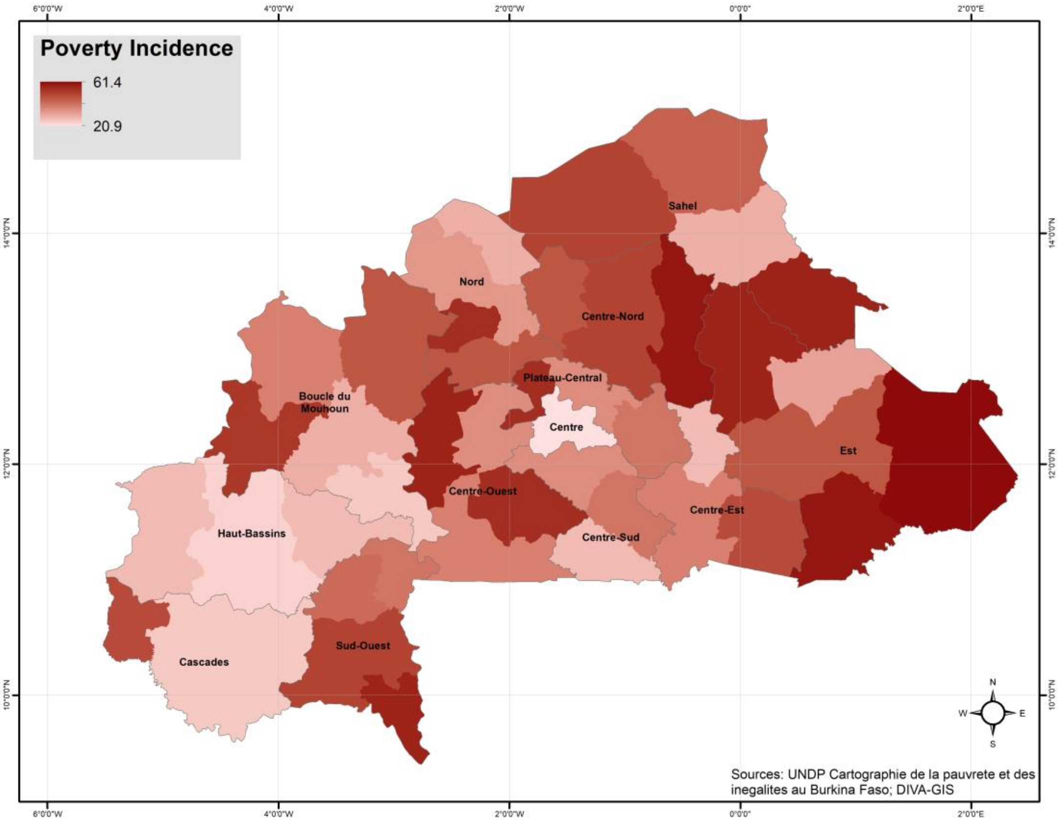


Figure 13. Burkina Faso: Poverty map (EICVM 2009)

To understand the spatial dimension of the food security situation in Burkina Faso, we present maps for stunting (Figure 14) and wasting (Figure 15) from the 2010 *Enquête Démographique et de Santé et à Indicateurs Multiples.* Stunting is the impaired growth and development that children experience from poor nutrition, repeated infection and inadequate psychosocial stimulation. Children are defined as stunted if their height-for-age is more than two standard deviations below the WHO Child Growth Standards median. On a population basis, high levels of stunting are associated with poor socioeconomic conditions and increased risk of frequent and early exposure to adverse conditions such as illness and inappropriate feeding practices. Stunting is prevalent in Burkina Faso with an estimated 34.6 percent of children considered stunted and 14.5 percent classified as severely stunted. Figure 14 shows that the problem is particularly severe in the Sahel and the Est, with over 40 percent of the children considered stunted (46.1 percent and 42.8 percent respectively) and over 20 percent classified as severely stunted (20.4 percent in both regions).

While stunting can be considered a longer-term indicator of poor socioeconomic conditions, wasting or low weight-for-height captures exposure to severe negative shocks (food shortages and disease) and can be used as a predictor of child mortality. Children are defined as wasted if their weight-for-height is more than two standard deviations below the WHO Child Growth Standards median. Wasting is prevalent in Burkina Faso with an estimated 15.5 percent of children considered wasted and 5.7 percent classified as severely wasted. Figure 15 shows the problem is particularly severe in the Centre-Nord and Centre-Est, with over 20 percent of the children considered wasted (24.7 percent and 20.6 percent respectively).

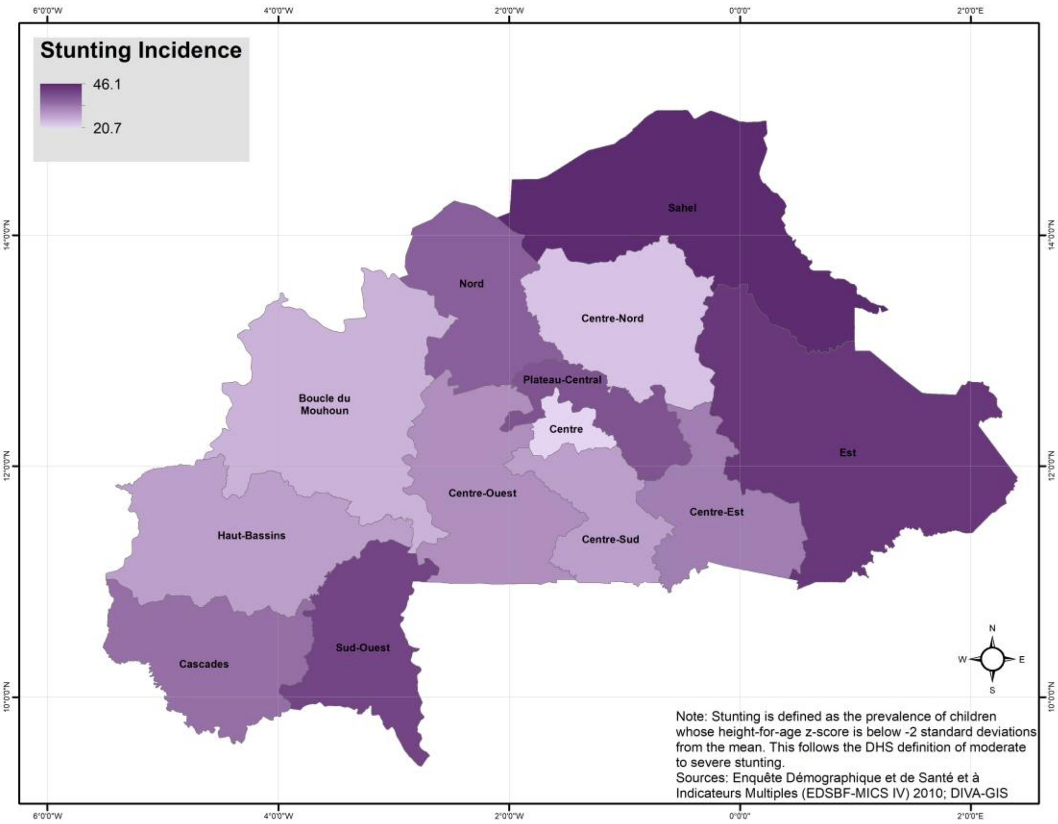


Figure 14. Burkina Faso: Stunting prevalence

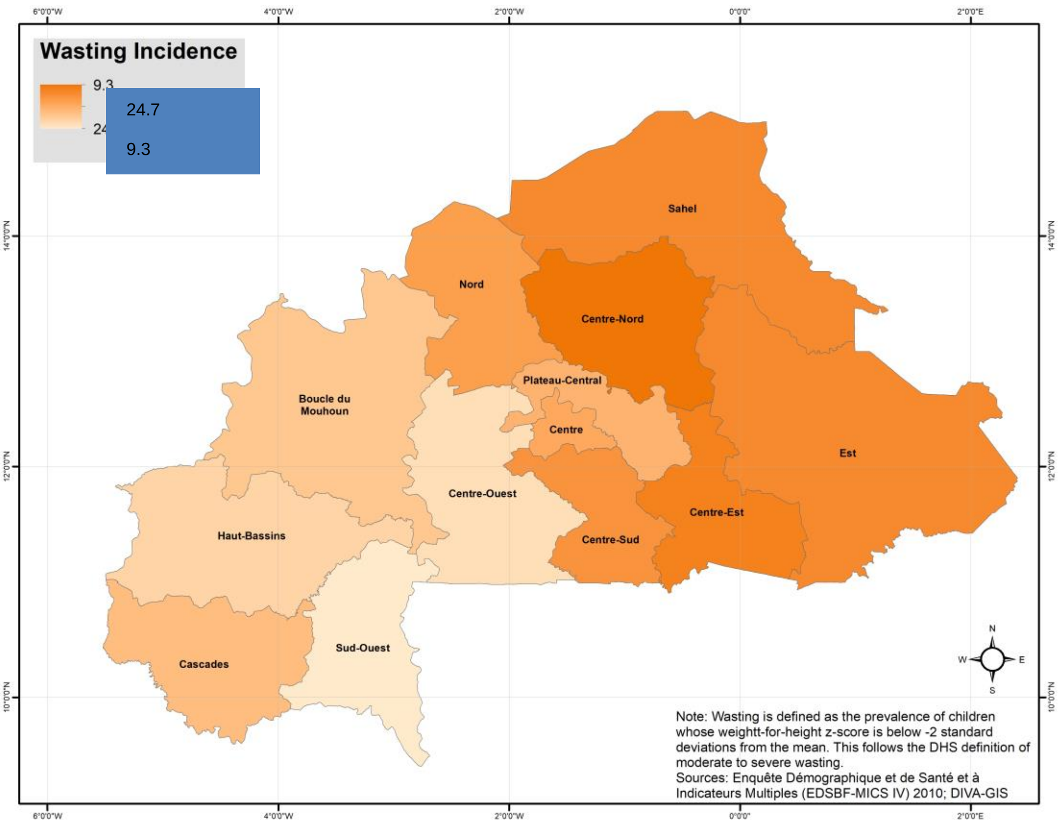


Figure 15. Burkina Faso: Wasting prevalence

The results in the previous sections identified the most attractive areas for investments in rural infrastructure by prioritizing areas with the highest expected gains in agricultural revenue from closing productive efficiency gaps. The maps in this section show that while the prioritization strategy that results from such criteria might not be perfectly aligned with policies aimed at reducing poverty and improving nutrition outcomes at the subnational level, some geographic synergies exist and should be considered. Our accessibility maps (Figure 9 and Figure 10) show, for example, that the Est and Sahel (the two regions with the worst stunting outcomes) should be prioritized for investments in improving and expanding the road infrastructure, but that in terms of closing efficiency gaps in agriculture, the Est offers much better opportunities.

5. Conclusions

In this study, we develop a spatial and economic tool for strategic analysis and visioning to help identify the best opportunities for investments in roads, small-scale irrigation, and rural electrification in Burkina Faso. For such investments to be effective for poverty alleviation, it is necessary that they lead to farm-level increases in productivity and are translated into higher incomes and better livelihoods for rural households. Our proposed approach utilizes stochastic frontier analysis (SFA) to identify areas of high agricultural potential with low accessibility to prioritize investments in road infrastructure, and (ii) estimate average household gains in agricultural efficiency by comparing smallholders' performance under current conditions and under separate scenarios of improved access to small-scale irrigation and rural electrification. Our analytical results and typology maps highlight the spatial heterogeneity in opportunities and priorities for road infrastructure, small-scale irrigation, and electrification investments.

In Burkina Faso, our results show a clear north – south divide in agricultural potential: the low agricultural potential in the north of the country results from unfavourable conditions for agriculture with the predominance of shrubs, savannah and steppe, characterized by rocky soils, and a short wet season that produces an average of 300 – 400 mm of rain per year in contrast with the south that receives more than 750 mm of rain. The agricultural efficiency map, on the other hand, shows an east – west divide, with higher efficiency regions appearing more often in the western part of the country. The combination of high agricultural potential in the south and high agricultural efficiency in the west is also consistent with the production patterns of major crops such as maize and rice. Superimposing the market access measure on the attainable agricultural potential estimates brings into focus two regions as priority areas for investments in expanding and improving the road network: the Est and Sud-Ouest regions, that combine medium to high access times to markets with medium to high attainable agricultural potential. The biggest gains in revenues from small-scale irrigation and rural electrification investments occur in the Sud-Ouest, Boucle du Mouhoun (Bale province), Centre-Est, and Est regions, while lack of access to water sources limits the potential for small-scale irrigation and the benefits from electrification in the Sahel region in the north.

References

Aigner, D. J., Lovell, C. A., & Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. Journal of Econometrics, 21-37.

Battese, J. E., & Corra, G. S. (1977). Estimation of a Production Frontier Model: With Application to the Pastoral

Briceño-Garmendia, C, & Domínguez-Torres, C. (2011). Burkina Faso's Infrastructure: A Continental Perspective. AICD Country Report, World Bank, Washington, DC.

Charnes, A., Cooper, W. W., & Rhodes, E. (1981). Evaluating Program and Managerial Efficiency: An Application of Data Envelopment Analysis to Program Follow Through. Management Science, 668-697.

Charnes, A., Cooper, W. W., Lewin, A. Y., & Seiford, L. M. (1978). Measuring the Efficiency of Decision Making Units. European Journal of Operational Research, 429-444.

FAPDA (2014). Burkina Faso Country Fact Sheet on Food and Agriculture Policy Trends. Retrieved from FAO: http://www.fao.org/3/i3760e/i3760e.pdf.

Gwilliam, K., Foster, V., Archondo-Callao, R., Briceño-Garmendia, C., Nogales, A., & Sethi, K. (2008). The Burden of Maintenance: Roads in Sub-Saharan Africa. AICD Background Paper 14, Africa Region, World Bank, Washington, DC.

Heckman, J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. Annals of Economic and Social Measurement, 475-492.

Kumbhakar, S. C., & Tsionas, E. G. (2008). Scale and efficiency measurement using a semiparametric stochastic frontier model: evidence from the U.S. commercial banks. Empirical Economics, 585-602.

Martins-Filho, C., & Yao, F. (2015). Semiparametric Stochastic Frontier Estimation via Profile Likelihood. Econometric Reviews, 413-451.

Mathematica Policy Research (2018). Evaluation of the Burkina Faso Agriculture Development Project: Baseline Report. Retrieved from: https://data.mcc.gov/evaluations/index.php/catalog/198/download/1179.

Meeusen, W., & van den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. International Economic Review, 435-444.

Ministère de l'Agriculture et des Aménagements Hydrauliques (2016). Rapport d'étude sur la typologie des entreprises agricoles au Burkina Faso.

Ministère de l'Economie et des Finance (2018). Agriculture, forestry, and fishing, value added (% of GDP) - Burkina Faso | Data

Park, B. U., & Simar, L. (1994). Efficient Semiparametric Estimation in a Stochastic Frontier Model. Journal of the American Statistical Association, 929-936.

Power Africa (2020). Burkina Faso – Power Africa Fact Sheet. Retrieved from https://www.usaid.gov/powerafrica/burkina-faso.

Sally, H., H. Lévite, and J. Cour (2011). Local Water Management of Small Reservoirs: Lessons from Two Case Studies in Burkina Faso. Water Alternatives, 365–382.

Tobler, W. (1993). Non-isotropic modeling speculations on the geometry of geography global spatial analysis. National Center for Geographic Information and Analysis, Technical Report 93-I.

USAID Burkina Faso (2015). "Fact Sheet: Agriculture and Food Security." Washington DC: USAID.

World Bank (2019). Burkina Faso Electricity Access Project (P166785). Burkina Faso Electricity Access Project (P166785). Concept Stage | Date Prepared/Updated: 24-Jan-2019 | Report No: PIDC25822.

World Bank (2007). Burkina Faso: The Challenge of Export Diversification for a Landlocked Country, Diagnostic Trade Integration Study for the Integrated Framework Program. Washington, DC: World Bank.

Xie, H., Perez, N., Anderson, W., Ringler, C., & You, L. (2018). Can Sub-Saharan Africa feed itself? The role of irrigation development in the region's drylands for food security. Water International, 43(6), 796-814.

Annex: Methodology

GIS market accessibility model

The market accessibility model applies spatial analysis using GIS variables to simulate the shortest amount of time it takes to travel between any two different points in the country. The model was developed on a raster format, where the entire area of analysis was converted into a grid of cells measuring 25 by 25 meters each. The first step to estimate the accessibility model is to assign each of these cells a *friction* value, which represents the time it takes to travel through the cell, based on the availability and quality of roads, the slope, and the presence of natural barriers.

Typically, roads in a network can be categorized as first order roads, second order roads, dirt road tracks, and walking trails. When first and second order roads are present in a cell, its crossing time can be calculated using the following equation:

$$\text{Cell crossing time (seconds)} = 92.6 \times \left(\frac{1}{\text{Speed (Km/hr)} \times \left(\frac{1000}{3600}\right)} \right) \quad (1)$$

Assuming specific travel speeds for first and second order roads (plus river navigation) results in the following cell crossing times:

Table A1. Average speed and cell crossing time by type of road (first and second order)

Type of road	Average travel speed (km/h)	Cell crossing time (secs)
First order road	60	5
Second order road	30	11

Source: Own elaboration

For roads classified as dirt road tracks and walking trails, the slope variable is used to calculate walking speeds. The walking velocity is calculated using the following equation from Tobler (1993):

$$\text{Walking velocity on footpath} = [6 \times \exp(-3.5 \times \text{abs}(S + 0.05))] \quad (2)$$

where S represents the slope. Finally, the walking velocity by type of road (dirt road, walking trail, and no road) is calculated as shown in Table A2.

Table A2. Average speed by type of road (dirt road tracks, walking trails, and no roads)

Type of road	Average speed (km/h)
Dirt road tracks	Walking velocity on footpath × 1.25
Walking trails	Walking velocity on footpath
No roads	Walking velocity on footpath × 0.6

Source: Own elaboration

Finally, the model considers the presence of natural barriers –in this case non-navigable rivers, which prevent people from traveling in a straight line unless there is a bridge. Cells corresponding to areas with a river and no bridge are assigned a travel time 10 times their value.

With the assumptions and equations presented above we build the friction model and allocate a travel time value to each cell. Then we run cost-weighted distance algorithms over the raster surface to choose the optimal route between any two points in the area of analysis that minimizes the accumulated travel time. To calculate this model, global geographic data on water, roads, railroads, topography, and natural barriers publicly available from DIVA-GIS is used. GIS land cover type data from NASA and the USGS is also used as an explanatory variable in the stochastic frontier estimation.

GIS water access and slope measures for the small-scale irrigation analysis

The biophysical suitability for small-scale irrigation is captured by two variables: the first denoting the accessibility to surface and ground water, and a second capturing the suitability of the slope for irrigation. These variables are inputs to the work done by Xie, et al. (2018) to predict irrigation expansion in Africa's drylands by 2050. The first step was to estimate the pixel-level suitability for small-scale irrigation, where small scale irrigation is defined as the use of treadle pumps, motor pumps, small reservoirs, and ponds managed by individuals or local communities. These suitability scores are then used, along with other inputs, to simulate the expansion of irrigation for the 2050-time horizons. Slope and water access are two of the criteria considered in creating the small-scale irrigation suitability index; the other criteria being proximity to existing irrigation and market access. We've included the slope and water access components of the index rather than the full small-scale suitability index because of our need to characterize the biophysical components of irrigation use rather than the market constraints, which are already included in the frontier estimation through market access and prices.

Water accessibility is measured on a scale from 0 to 100 where a score of 100 is given if the area is within the spatial extent of surface water bodies indicated by the Global Lakes and Wetlands Database level-3 database. This is a database developed by WWF and the Center for Environmental Systems Research at the University of Kassel that contains the maximum extent of permanent surface water bodies, including lakes, rivers, reservoirs, and wetlands. If a location is outside of this area, then the suitability is determined by the accessibility of ground water as categorized by the British Geological Survey's digital ground water depth map of Africa. A score of 70 is given if the groundwater is very shallow, 40 if it is shallow, 20 if it is medium shallow, and 0 if it is medium. FigureA1 shows the water access index map for Burkina Faso. Most of the land area of the country is considered to have moderate suitability for irrigation in terms of water access with approximately 62 percent of the area given an index value of 40. Approximately 24 percent of the area is considered suitable or highly suitable with a score of 70 or higher.

Similarly, slope is measured on a scale between 0 and 100 where 100 denotes most suitable and 0 indicates unsuitable. We use the WWF's HydroSHEDS Digital Elevation Model (DEM). An area is given a score of 100 if the grade is less than 2 degrees, 70 if the grade is between 2 and 4 degrees, 40 if it is between 4 and 7 degrees, 20 for areas between 7 and 10 degrees, and a value of 0 is assigned if the grade is greater than 10 degrees. FigureA2 shows the slope index map for Burkina Faso. 84 percent of the land area of the country has a slope of less than 2 degrees and is given an index value of 100 while only 1 percent has a slope of 7 degrees or higher.

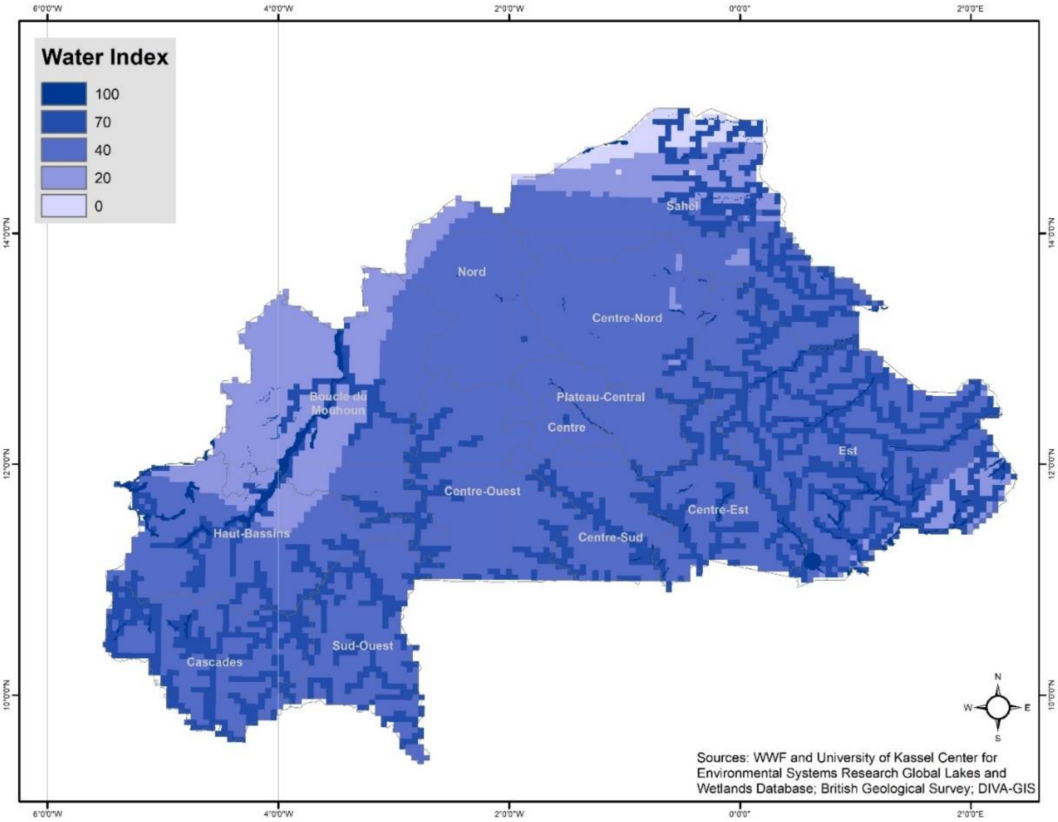


Figure A1. Burkina Faso: Water access index

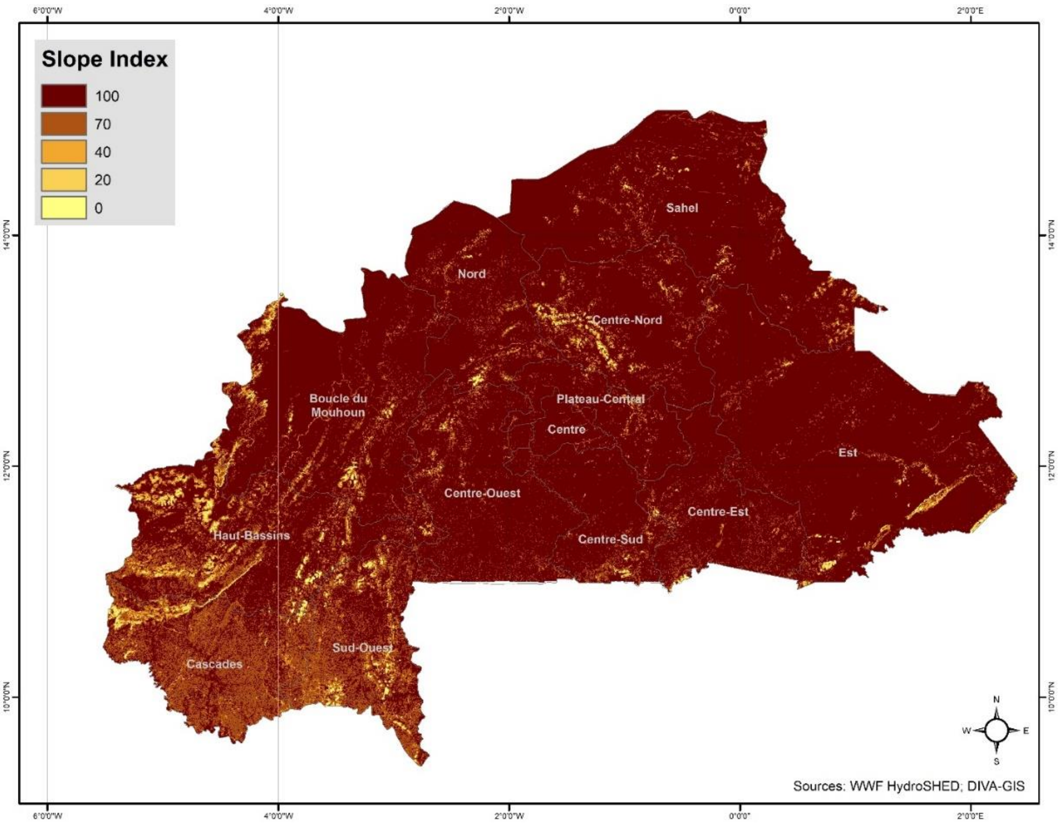


Figure A2. Burkina Faso: Slope index

Heckman selection model for the rural electrification analysis

To assess the impact of increasing access to electricity on smallholders, we first need to estimate what would the electricity consumption be for those households that do not have access to the service yet. Therefore, we need to estimate the following underlying relationship:

$$ec_i = h_i\gamma + \mu_{1i} \tag{3}$$

where ec_i is the electricity consumed by household *i* during a given period, h_i is a vector of household characteristics, and μ_{1i} is an error term distributed $N(0,\sigma)$. However, electricity consumption is only observed if the household is connected to a service provider if:

$$q_i\theta + \mu_{2i} > 0 \tag{4}$$

where q_i is a vector that includes factors that determine whether household *i* is connected to a service provider, μ_{2i} is an error term distributed $N(0,1)$, and $\mathrm{corr}(\mu_1, \mu_2) = \rho$.

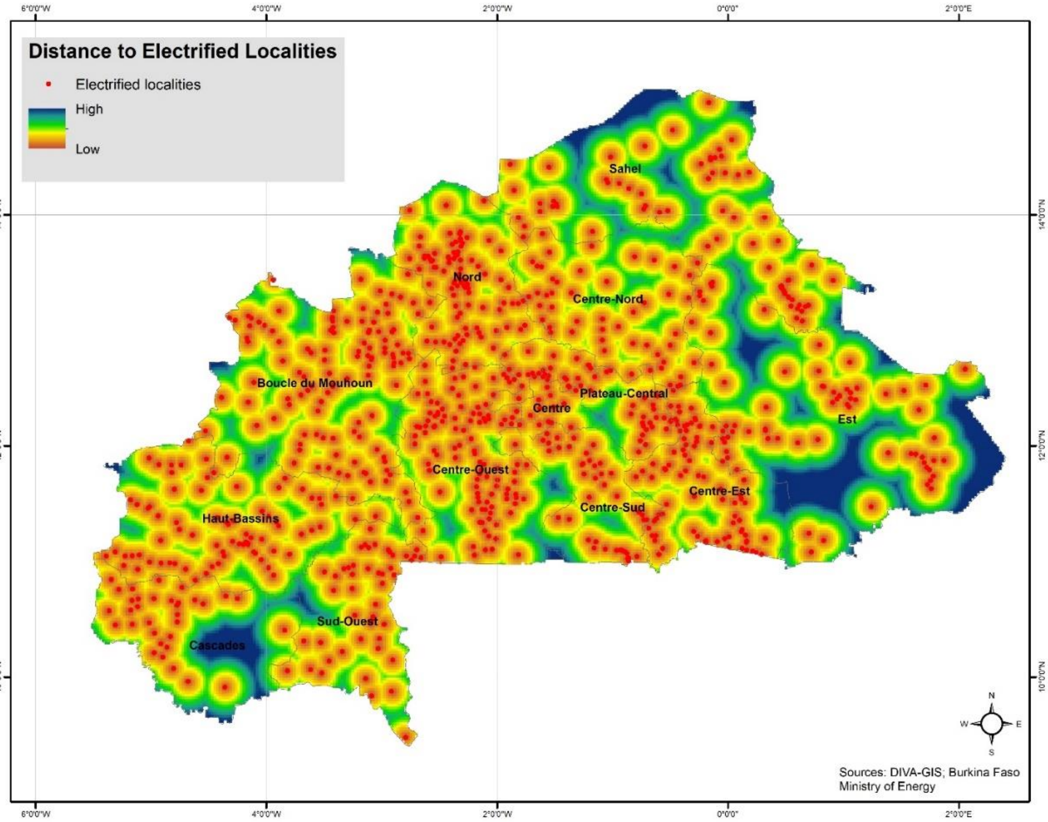


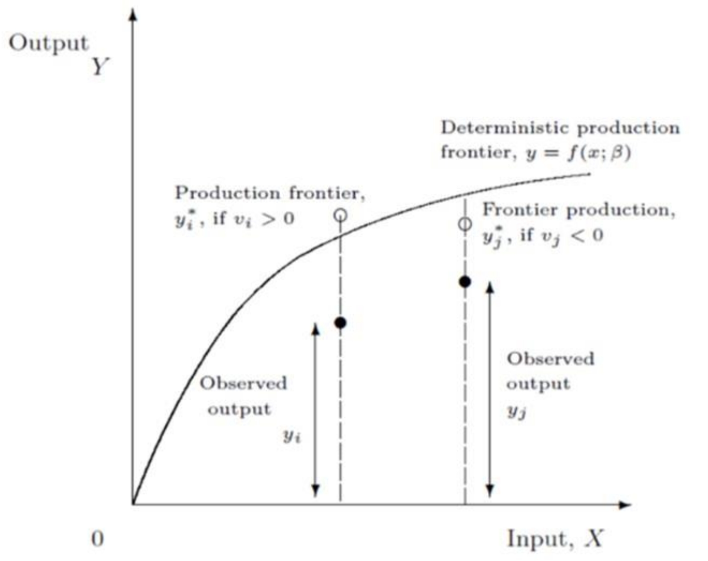
Figure A3. Burkina Faso: Distance to electrified localities

Heckman's approach (Heckman, 1976) provides consistent, asymptotically efficient estimates for all the parameters in this model if variables that strongly affect access to electricity but not consumption can be found. Given the available data, we use the average distance to the nearest electrified locality (Figure A3A3) for Burkina Faso as a measure that explain access to electricity, but not directly determine consumption.

Stochastic frontier analysis

The two most commonly used methods to estimate the efficiency of production units are data envelopment analysis (DEA) (Charnes, et al., 1978; 1981) and stochastic frontier analysis (SFA) (Aigner, et al., 1977; Meussen & van den Broeck, 1977; Battese & Corra, 1977). DEA is a non-parametric approach that uses linear programming to identify the efficient frontier, while SFA is a parametric approach that hypothesizes a functional form and uses data to econometrically estimate the parameters of that function.[2] Both methods measure efficiency as the distance between observed and maximum possible (frontier) outcomes, but the key advantage of SFA for our purposes is that, unlike DEA, it allows to separate random noise in the error term from the actual efficiency score which is an important feature when analyzing agricultural activities constantly exposed and extremely sensitive to random shocks. DEA estimates a deterministic frontier that incorporates the noise as part of the efficiency score, which is more appropriate when analyzing decision making units such as banks or factories.[3]

The SFA approach allows the econometric exploration of the notion that, given the fixed local agroecological and economic conditions in a micro-region and the occurrence of random shocks that affect agricultural production (weather, prices, etc.), the investment and production decisions a farmer makes translate into higher or lower production and income. In such a context, inefficiency is defined as the loss incurred by operating away from the frontier given the current prices and fixed factors faced by the household. By estimating where the frontier lies, and how far each producer is from it, the stochastic frontier approach helps to identify local potential and efficiency levels to construct the typology. A graphical depiction of this concept is shown in Figure A4.



Source: Own elaboration

Figure A4. Illustration of the stochastic production frontier in the single-output, single-input case

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[2] See Park & Simar (1994), Kumbhakar & Tsionas (2008), and Martins-Filho & Yao (2015) for semi-parametric approaches to SFA that relax some of its parametric functional form requirements.
[3] The main cost of using SFA is that it requires more detailed data to model the efficiency term and, as in any parametric approach, it relies on making the correct choice of functional form.

Using the basic model proposed by Aigner, et al. (1977) and Meeusen & van den Broeck (1977) the stochastic frontier production function is defined as:

$$y_i = f(x_i;\beta)\exp(v_i - u_i) \qquad (5)$$

where y_i is the possible production for farmer *i*, $f(x_i;\beta)$ is an adequate function of inputs x and parameters β, v_i is a random error with zero mean, associated with random factors that are not under the farmer's control, and u_i is a non-negative random variable associated with factors that prevent farmer *i* from being efficient.

Then the possible production y_i is bounded by the stochastic quantity $f(x_i;\beta)\exp(v_i)$. It is assumed that the stochastic errors v_i are i.i.d. random variables distributed $N(0,\sigma^2)$, and independent from u_i. A farmer's technical efficiency is defined as the fraction of the frontier production that is achieved by his or her current production.

Given the frontier production of farmer i is $y_i^* = f(x_i;\beta)\exp(v_i)$ then his or her technical efficiency can be defined as:

$$TE_i = \frac{y_i}{y_i^*} = \frac{f(x_i;\beta)\exp(v_i - u_i)}{f(x_i;\beta)\exp(v_i)} = \exp(-u_i) \qquad (6)$$

Caudill & Ford (1993) and Caudill, et al. (1995) showed that the presence of heteroskedasticity in u_i is particularly harmful because it introduces biases in the estimation of β and technical efficiency. This is very likely to occur if there exist sources of inefficiency related to factors specific to the producer. In this case the distribution of u_i will not be the same for all the observations in the sample and a correction for heteroskedasticity needs to be made by modelling the variance of u_i:

$$\sigma_{u_i}^2 = \exp(z_i\delta) \qquad (7)$$

where z_i are farmer-specific factors affecting his or her technical efficiency.

To estimate the model expressed by equations (3) - (5) it is necessary to address the fact that farms are multi-output production units, making it necessary to move from a production function to a profit or revenue function approach. The stochastic frontier profit function can be expressed as (Kumbhakar & Lovell, 2000):

$$\pi_i = f(p_i, w_i;\beta)\exp(v_i - u_i) \qquad (8)$$

where p_i and w_i are output and input price vectors, respectively.

Farm-specific characteristics and conditions in which its productive activities take place affecting the smallholder's technical efficiency and determined by decisions made at the local level by the household or community in the short term are included in the vector z_i, referred to in (7). Typically, the effect of factors included in z_i cannot be captured by a price or set of prices due to market failures often found in the context of agricultural activities in developing countries. For this study, we incorporate the following variables of z_i in the econometric analysis:

- *Farm size*: Number of hectares of land managed by the farmer. In contexts where smallholders have little access to land and credit markets (or these are not properly developed) the effect of land and land availability cannot be fully captured with the price of land in the deterministic portion of the stochastic frontier. Therefore, the amount of land the farmer currently manages restricts his scale and is a source of inefficiency that needs to be included in the error term.

- *Farm assets*: Value of farm assets to proxy for other capital inputs.
- *Household size*: Number of household members. The small scale and low revenue stream of many of these farms does not always allow them to hire labor to adjust their scale to seasonal changes and market trends, which makes them rely more heavily on the household's labor supply.
- *Characteristics of the household head*: Depending on each particular context, the gender and education of the household head can proxy for the farmer's access to information and opportunities that affect the performance of the productive unit.

In addition to these factors, in an agricultural context it is necessary to consider other conditions that affect the farm's potential that cannot be easily modified in the short or medium term, such as the climate or soil quality. For this reason, the farm's potential or frontier is adjusted using GIS data on agroecological zones or agricultural land use types. These variables are introduced as shifters of the deterministic portion of the frontier so (8) becomes:

$$\pi_i(p, w, AEZ) = f(p_i, w_i, AEZ_i; \beta)\exp(v_i - u_i) \tag{9}$$

where AEZ are the agroecological zone variables.

Assuming a Cobb-Douglas production function the normalized profit or revenue frontier function for the single output case estimated through maximum likelihood is:

$$ln\frac{\pi}{p} = \delta_0 + \sum_n \delta_n \, ln\frac{w_n}{p} + \sum_q \delta_q AEZ_q + v_\pi - u_\pi \tag{10}$$

To estimate Equation 10 the data requirements are a recent household survey representative at the national and sub-national levels, that includes information on farm revenues, agricultural prices, and farm and household characteristics, as well as GIS on local agroecological characteristics, such as land use, as well as for market access measures. For Burkina Faso, we use household level data from the 2014 *Enquete Multisectorielle Continue* (EMC).