Does Agricultural Intensification Enhance Rural Wellbeing? A Structural Model Assessment at the Sub-Communal Level: A Case Study in Tunisia

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Abstract: We examined the impact of agricultural intensification on the wellbeing of rural communities in a developing country on a sub-communal scale. To measure the interactions within this complex causal relationship, a statistical approach was applied, using partial least squares path modeling (PLS-PM) in its formative structure. Using PLS-PM to simultaneously relate the measured variables (manifest variables) and conceptual variables (latent variables), while incorporating other variables, such as the bioclimate and demography, we characterized the spatial structure of the links between intensive agriculture and wellbeing. The aim was to facilitate government intervention aiming to improve the wellbeing of rural households, while avoiding cumbersome and costly surveys when the scope of public action is extended to a region or a country. Our findings show that the generalization of the productivist system is not always appropriate in developing countries. In our case study, employment in the secondary and tertiary sectors is insufficient to accommodate the rural exodus. In such situations, agricultural intensification leads to poverty and migration to the areas of production and increases disparities in social wellbeing in rural areas.

Keywords: agricultural intensification; rural wellbeing; developing country; partial least squares path modeling; Tunisia

1. Introduction

Since the advent of the Green Revolution in Latin America and South Asia in the 1960s and its coupling with the International Monetary Fund and structural adjustment policies of the 1980s, intensive agriculture has become the cornerstone of agricultural development programs and policies aiming to spur economic growth in developing countries [1]. This intensification of agricultural practices, supported by public policies [2,3], generally leads to crop specialization through the selection of new high-yielding varieties (HYVs), combined with synthetic inputs, mechanization, and new irrigation systems. Intensification has been a major factor in the tremendous increases in food production [1,4,5]. In terms of social benefits, the Green Revolution has contributed to reducing poverty on a large scale, fighting hunger for millions of people, and converting thousands of hectares of land into agricultural crops [5]. However, the debate on how rural wellbeing is impacted by agricultural intensification is still unresolved. Beyond the obvious environmental and human health concerns [6], studies at the local level in Africa reveal that agricultural intensification programs exacerbate gender and class inequalities, resulting in environmental degradation, impediments to food sovereignty, and little apparent benefit to rural communities, while benefiting large-scale farmers, urban populations, and agribusiness [7–13]. In contrast, some studies on the wellbeing of smallholder farmers in Zambia have shown that adopting improved maize varieties tends to increase crop yields, food security, and household income.
A crucial issue, therefore, is how to assess the impact of agricultural intensification on the rural population’s wellbeing. This is especially challenging, since wellbeing is multi-dimensional, while poverty or inequality are usually identified by one-dimensional indicators, usually based on monetary variables [14]. However, since the publication of the World Human Development Report in 1990, emphasis has been placed on several dimensions other than income that can affect the level of individual wellbeing. The UNDP Human Development Report of 2010 proposed a composite indicator, the human development index (HDI) [15], to evaluate countries’ human development rate. This indicator measures not only per capita income growth but also more qualitative factors involved in building human capital (health, education, food security, and gender equity) [16]. The 2019 UNDP report “Beyond income, beyond averages, beyond today” [17] highlights inequalities other than income: any assessment must consider money, but it must also go beyond this to include other inequalities, such as those in health and education. Attempts to go “beyond income” include the Canadian Index of Wellbeing (CIW), the OECD’s Better Life Index, and Bhutan’s Gross National Happiness Index [18]. The findings suggest that cultural identity, inequality, job security, health, community vitality, leisure, environmental factors, and subjective perceptions are equally important factors in shaping a population’s wellbeing [19,20]. Wellbeing thus includes not only material but also other interdependent dimensions, including the relational dimension and the subjective dimension, which concerns the individual, social, and cultural norms and values that influence people’s preferences and behavior [21]. Despite conceptual progress towards agreement on the universally relevant dimensions of wellbeing, consensus is still lacking on the question of how to translate these into locally appropriate indicators so as to measure wellbeing in different contexts [22].

Studies generally construct a composite index of wellbeing, mainly rooted in Sen’s capability approach [23] based on non-monetary indicators, such as durable goods, housing conditions, and education, or a bi-dimensional analysis of poverty based on income and housing [24]. However, Sen’s capability approach incorporates a set of wellbeing factors related to the quality of human existence within a formal and quantitative methodology. This requires access to rarely available quantitative variables that reflect fundamental aspects of wellbeing (employment rates in the agricultural sector, schooling, health, and access to drinking water, as well as women’s employment). In addition, critics of the HDI point out the weaknesses of this analytical approach from the perspective of the spatial distribution of human development [25]. The issue is that the indicators used at the international level do not always seem to be relevant at the local level, especially when applied to rural areas [26].

This problem can be solved by reducing the target areas from the national to communal or sub-communal levels. As Jalan and Ravallion [27] showed, the greatest poverty reduction is achieved when the target areas are villages or municipalities. Baker and Grosh [28] also found that the smaller the target areas were, the greater the potential for poverty reduction was. Moreover, the lack of attention given to the collective dimension of wellbeing diminishes the effectiveness of this indicator in developing countries, especially in African contexts. Indeed, as Evans and Prillelrens [29] pointed out, collective wellbeing is realized through universal access to quality health care and public education and depends on policies that promote social justice, distributing resources through progressive taxation systems in turn.

While the literature has focused on the impact of agricultural intensification on the living conditions of the rural population, we hypothesize that intensive agriculture can have a negative impact on their overall wellbeing. Using partial least squares modeling (PLS-PM) allows us to estimate the effects of unmeasured factors or latent variables that have proven to be effective indicators of complex causal relationships. Here, this approach is applied to the relationship between agricultural intensification and the level of wellbeing of the rural population, going beyond the income of the intensive farmers themselves in order to incorporate other control variables, such as demography and the bioclimate. To
test its robustness, we applied our methodology to rural areas in northwestern Tunisia on the sub-communal scale.

The paper is organized as follows: Section 2 describes the case study area, the methodology used, and the variables built. Section 3 presents the results of our empirical assessment of agricultural intensification’s impact on the rural population’s wellbeing. The relevance of this research and its limitations are discussed in Section 4.

2. Materials and Methods

2.1. Study Area

Tunisia is a Mediterranean country located in eastern North Africa between Algeria (to the west) and Libya (to the south). It covers a total area of 164,000 km\(^2\), of which 30% (4,800,000 ha) forms a usable agricultural area (UAA). Tunisia is characterized by a Mediterranean climate with a mild winter and a hot summer. It is located at the end of the eastern part of the Atlas Mountains, mainly within the northern part of the Sahara Desert.

From the beginning of the country’s independence to its liberalization in the 1980s, agricultural policies in Tunisia have favored intensive and export-oriented agricultural systems. Under the impetus of the Green Revolution, Tunisian authorities encouraged the importation of high-yielding hybrid seed varieties from CGIAR centers, notably CIMMYT in Mexico [30,31]. These were intended to modernize and intensify the cropping systems, with the aims of creating a surplus in the agricultural sector to replace imports and turning its work force and production (food and raw materials) into a modern urban-industrial sector [32–34]. The restructuring of agricultural production greatly increased the population’s dependence on “standard” seed varieties, leading to the disappearance of a large variety of local seeds adapted to the local climate and drought [35].

A simultaneous effect of this technological trend was enhanced territorial heterogeneity. Tunisia has long suffered from rural migratory movement, especially that from the northwestern regions. This migration stems from the agrarian crisis, particularly affecting the Medjerda Valley and the Kef plains, as well as the rapid development of mechanization and the evolving farming system [36,37]. To address these problems, in 1984, Tunisia adopted a new regional policy called the “Integrated Rural Development Program” (IRDP), targeting less favored areas [38]. These regional programs led to a substantial reduction in the level of poverty and improvements in Tunisia’s basic infrastructure, especially in rural areas, with better access to drinking water, electricity, and sanitation [39]. However, Tunisia’s agricultural regions remain those where poverty is the most pronounced, especially the central-western and northwestern parts of the country [40–42]. Outstanding are the governorates of Kef, Kassrine, and Beja, where poverty reaches, respectively, 34.2%, 32.8%, and 32% [41].

The study was conducted in the Northwest region (Figure 1), delimited to the west by the Tunisian-Algerian border, to the east by the capital, and to the north by the Mediterranean Sea. The region is composed of four governorates (sets of municipalities): Beja, Jendouba, Kef, and Siliana. It accounts for 19% of the country’s exploitable agricultural area and exemplifies Tunisia’s regional paradox: that of a rich region in terms of water resources and agricultural production, yet with extremely poor inhabitants [33]. This agricultural region is renowned for its fertile land and large water reserves due to its agro-pedoclimatic conditions and, in particular, its annual rainfall, approaching 400 mm (some years as high as around 1000 mm). In terms of agricultural production, the governorate of Beja produces almost 18.62% of the country’s cereals and 12.5% of its vegetable crops [43]. However, it also has one of the lowest levels of human development in terms of education, health, employment, and infrastructure [44]. For instance, the unemployment rate among young people (18–24 years old) is 33.8% in the Northwest. According to figures released by the Department of Water and Rural Drinking Equipment of the Ministry of Agriculture, some 300,000 people still do not have access to drinking water, mainly in rural areas [45].
2.2. Methodology

Our aim was to assess the relationship between intensive agriculture and wellbeing in rural areas of the Northwest region of Tunisia, where agriculture and its dependent populations are concentrated. We implemented a structural model, a partial least squares path modeling (PLS-PM) approach, enabling us to incorporate both the available data and the unmeasured factors.

2.2.1. Partial Least Squares Path Modeling

The partial least squares path modeling (PLS-PM) approach enables the effects of an unmeasurable phenomenon to be assessed using structural equation modeling [46] and a set of available indicators (income, health, education level, yields, chemical input use, irrigation, etc.) [47]. It is well-suited to exploratory analyses [48]. The PLS-PM structural equation model can be implemented via two sub-models (see Figure 2): (1) the structural model or inner model, which explains the relationship between endogenous latent variables (LV) and (2) the measurement model, or the outer model, which specifies the relationships between an LV and its observed or manifest variables (MV) [49], i.e., the LV is a non-observable variable (or construct) and can be described by a set of manifest variables (MV) [50]. In the inner model, the connections between LVs are quantified through path coefficients (β), while the links between LVs and MVs in the outer model are quantified through weights (W) [51] (Figure 2).
The path coefficients represent the influence of exogenous (independent) variables on endogenous (dependent) latent variables. The measured score of an LV (LVm; Equation (1)) is the weighted sum of the scores corresponding to the VM. The predicted score of an endogenous LV (for example, LVp,c; Equation (2)) is the weighted sum of all the associated exogenous latent variables, where the weights are now represented by path coefficients [47]:

$$LV_m = \sum_{i=1}^{n} (MV_i - Wi)$$

$$LV_{p,c} = LV_m, a \times \beta_{ac} + LV_{mb} \times \beta_{bc}$$

PLS-PM can handle both formative and reflective measurement models. In a reflective measurement model, the construct is the cause of the indicators. In a formative model, the indicators cause or form the construct (see Figure 1). In cases where the indicators do not reflect the theoretical construct but rather combine to produce it, a formative measurement model is appropriate [52,53]. The formative perspective distinguishes many of the complex measures used in the economic literature. Examples include the index of sustainable economic welfare [54], the human development index [55], and the quality of life index [56].

In socioeconomic analyses such as the present study, models are mainly conceived as formative constructs generated by a weighted linear combination of indicators such as income, employment, educational attainment, and place of residence [57,58]. To better evaluate the relevance of the formative constructs, we followed three indices or quality metrics adapted from Diamantopoulos and Winklhofer [59]. The first step was to precisely define the domain of the studied constructs and then to ensure that the indicators covered the whole of this construct. We based our definition on theory to ensure a sufficient representation of the studied concepts. The second step involved determining whether the structural relationships were meaningful by measuring the coefficient of determination, R2, of the endogenous constructs. In this sense, R2 indicates the degree of variance in the dependent latent variable as explained by its independent variables (see Figure 1). To evaluate the level of collinearity between formative indicators, we calculated the variance...
inflation factor (VIF) to detect potential failures in the adjustment of the training set that could impact the estimation of the parameters (weights and path coefficients) [47]. This step ensures the external validity of the model by examining the outer model weights and the relative contribution of the measured variables to the definition of their corresponding latent variables [49]. In the last step, we assessed the overall validity of this complex model through the goodness-of-fit index (GoF) [60].

Each LV was measured at three structural relationship levels, drawing on a formative measurement model set-up:

- In the first step, causal relationships between the MVs used in the structural model were assessed by estimating the path coefficients [51]. In this step, we assessed the quality of the structural model: the R2 coefficient was used to measure the model’s predictive accuracy, and the variance inflation factor was used to control for collinearity bias (VIF \(=\frac{1}{1-R^2}\)).

- Then, the mediation relationships in the PLS-PM model were analyzed to explore the degree of causality in the assessed relationships, thus indicating the strength of the direct and indirect effects. The external validity was verified through the outer model weights (Figure 2).

- The last step consisted of assessing the overall validity of the model through the goodness-of-fit index. The GoF was calculated using the square root of the geometric mean of the average communality multiplied by the average R2 (Gof \(=\sqrt{\text{communality} \cdot R^2}\)) [60].

Finally, PLS-PM enables the spatialization of the results through cluster analysis. Cluster analysis is based on the causal relationships of the variables with the results, the most significant of which are grouped by statistical proximity (formally, clusters). It then enables the clusters to be spatialized on the database scale by locating the dominant cluster in each geographical base element.

2.2.2. Latent and Manifest Variables

The similarity of the information provided by the manifest variables was estimated, enabling us to identify 18 VMs corresponding to a block of 4 LVs (Table 1). This estimation is based on correlation matrices (see Appendix A), as follows:

- “Agri-intensive”: This variable served three purposes. Firstly, it described intensive agriculture more broadly than the standard variables (size of the farms, commodity supply, incomes). Secondly, it served as a baseline for our wellbeing impact assessment. Thirdly, it enabled us to link this system of agricultural production with all the climatic conditions and the factors related to rural society transformations stemming from the modernization of the agricultural sector (rural exodus, feminization, etc.). We used yield statistics derived from the quantities produced and amounts of surface area involved in the production of three major crops (vegetables, wheat, and arboriculture), considering two production systems (irrigated high-input vs. rainfed low-input): ti for the irrigated portion of crops and th for the rainfed, high-input portion of crops (sources: Spatial Production Allocation Model data (SPAM)) [61].

- “Wellbeing”: A local welfare index was used to quantify the rural population’s quality of life using statistical studies based on non-monetary attributes. The variables were chosen to reflect fundamental aspects of wellbeing other than income in rural areas: the employment rate in the agricultural sector, schooling, health and access to drinking water, and women’s employment, with reference to the UNDP human development index (sources: databases of the National Institute of Statistics of Tunisia) [13,17,23,62].

- “Bioclimate”: Climate factors are among the most important natural indicators (especially rainfall) in developing countries such as Tunisia, with a direct impact on agricultural yields. Two of the prime factors are precipitation and temperature (in our case, for 1970–2000). Bioclimate variables were derived from monthly temperature and rainfall values to render them more biologically meaningful. They represent extreme or limiting climatic factors [63]: the temperature of the coldest and warmest month
and the precipitation of the wettest month and wettest quarter (sources: databases of the Global Digital Elevation Model and WORLDCLIM database).

- “Demography”: This variable refers only to the population in rural areas. The data used come from two main sources: the first is the DIVERCROP project (https://divercropblog.wordpress.com, accessed on 1 December 2020), and the second is the general census of the population in 2014 [64].

Table 1. Measured variables used for the partial least squares path modeling.

<table>
<thead>
<tr>
<th>Latent Variable</th>
<th>Measured Variable</th>
<th>Units</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agri-intensive</td>
<td>Y-th-wheat</td>
<td>Cell 10 km</td>
<td>Yield statistics derived from quantities of major agricultural products, vegetables, wheat, and arboriculture, produced by two production systems: -ti high-input: crop production with area equipped for either full- or partial-control irrigation using improved inputs, such as modern seed varieties and chemical fertilizer, as well as advanced management, such as soil/water conservation measures; -th rainfed high-input: Rainfed crop production using high-yield varieties and the optimal application of fertilizer, chemical pesticides, disease, and weed controls that may be fully mechanized.</td>
<td>Maps SPAM 1</td>
</tr>
<tr>
<td></td>
<td>Y-th-pulse</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Y-th-arbo</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Y-ti-whea</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Y-ti-vege</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bioclimate</td>
<td>Alti-min</td>
<td>Meters</td>
<td>Minimum altitude by cell</td>
<td>Global Digital Elevation Model 2</td>
</tr>
<tr>
<td>BIO6</td>
<td>Cc</td>
<td></td>
<td>Min temperature of coldest month</td>
<td>WORLDCLIM database 3</td>
</tr>
<tr>
<td>BIO8</td>
<td>Cc</td>
<td></td>
<td>Mean temperature of wettest quarter</td>
<td></td>
</tr>
<tr>
<td>BIO13</td>
<td>Mm</td>
<td></td>
<td>Precipitation of wettest month</td>
<td></td>
</tr>
<tr>
<td>BIO16</td>
<td>Mm</td>
<td></td>
<td>Precipitation of wettest quarter</td>
<td></td>
</tr>
<tr>
<td>Wellbeing</td>
<td>Employ-agri</td>
<td>%</td>
<td>Employment rate of rural population in agriculture</td>
<td>General census of population and housing 2014 4</td>
</tr>
<tr>
<td></td>
<td>Employ-rate _w</td>
<td>%</td>
<td>Employment rate of women in agriculture</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Water</td>
<td>%</td>
<td>Rate of rural population’s access to drinking water</td>
<td></td>
</tr>
<tr>
<td></td>
<td>School</td>
<td>%</td>
<td>Rate of rural population’s access to schooling</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Health</td>
<td>%</td>
<td>Number of inhabitants per doctor (by thousand)</td>
<td>Hyde database 5</td>
</tr>
<tr>
<td>Demography</td>
<td>Density</td>
<td>Inhabitant/km²</td>
<td>Percentage of rural population (rural population by cell × 100)/total population by cell</td>
<td>General census of population and housing 2014</td>
</tr>
<tr>
<td></td>
<td>Pop-rural</td>
<td>Cell 10 km</td>
<td>Difference between number of people migrating to and number of people migrating from a given rural area during a given period</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Migration</td>
<td>Cell 10 km</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3. Results

The LV bioclimate was considered exogenous (independent variable), meaning that statistical inferences between the LVs were assessed based on it, while the other LVs—Agri-intensive, Demography, and Wellbeing—were considered endogenous (dependent latent variables).

3.1. External Validity: Outer Model

The contribution of each MV to explaining the structure variation in the formative structure was assessed using outer weights to identify the effect of each latent variable in the theoretical structure (as the sum of the direct and indirect relationships), as described above (Figure 3).

![Diagram of PLS-PM](image)

**Figure 3.** Diagram of PLS-PM. (A) summarizes the various structural regressions of the causality model. Circles represent the latent variables, namely “Bioclimate”, “Agri-intensive”, “Wellbeing”, and “Demography”. (B) represents the formation variables (rectangles). Arrows represent links between formation variables and associated latent variables, as well as those between related latent variables, while the arrow labels are the weights and path coefficients that quantify those links.

We can see some significantly intuitive relations, such as the negative impact of migrations on demography when the density has a positive effect. Some weights are weak and thus show little effect on their constructs. In addition, the variables of rainfed high-input wheat production ($y_{th\_wheat} = 0.99$) and irrigated vegetable production ($y_{ti\_vege} = 0.64$) are given positive weights in the model. Unsurprisingly, this means that their contributions to Agri-intensive are greater than those of the rest of the crops.

Obviously, lower levels of employment, health, and access to drinking water imply lower wellbeing. However, there are three surprising negative relationships: those with agricultural employment, the rate of women’s employment, and health. The explanation should be sought in the overall interactions between these factors, keeping in mind Tunisia’s
regional paradox: a high level of agricultural production coupled with a high level of poverty. To illustrate how the wellbeing of the rural population can be impacted by basic social factors such as health, employment, education, and access to drinking water, an interesting variable is the share of women in agricultural employment. The rural part of northwestern Tunisia is characterized by a high rate of female employment in agriculture, mainly in intensive farming [65], which can be interpreted as positive (higher family income). However, our wellbeing indicator highlights a negative effect on wellbeing (Figure 3), for which there are two possible explanations. The first is the feminization of the agricultural sector involving activities that rely on an intensive workforce with a very low level of education, low wages, and no health coverage [66,67]. The second is a huge male exodus from rural areas to the cities or abroad (this exodus has a negative effect on wellbeing in the source region). Lastly, our results show the importance of schooling for the wellbeing of the rural population. In Tunisia, the educational system is free and compulsory, which has enabled universal education. The enrollment rate for 6–14-year-olds reached 95.2% in 2006, with substantial equity between girls and boys. Despite these efforts, at regional level, there are disparities that call for correction, especially considering the worrying secondary school drop-out rates in some governorates.

3.2. Geographical Distribution of Spatial Units Connected with Intensive Agricultural Areas

In a second step, we conducted a cluster analysis of the latent variable scores to identify the spatial relationships between the latent variables. The cluster analysis was implemented according to the following methodological protocol: (1) the creation of a spatialized database using the spatial divisions defined by the Divercrop program (10 km pixel resolution), composed of homogeneous and exhaustive data for the whole Northwest region of Tunisia; and (2) the spatialization of the results of the PLS-PM model (see Figure 3) using GIS software (Arcgis/Qgis). We identified and characterized four classes of spatial units, labeled as Clusters 1 to 4:

Cluster 1: This class covers the largest areas of modern and productive agriculture ($y_{ti\_wheat}$, $y_{ti\_vege}$, $y_{th\_pulses}$, $y_{th\_arbo}$), with all the most strategic agricultural activities of the country. Despite such natural and economic potential, this class is also where the living conditions of the rural population are the most unfavorable in terms of access to basic public services (hospitals, schools, water sanitation), with high rates of unemployment ($Employ\_agri$).

Cluster 2: This class presents the highest population density (e.g., Beja, Kef, Medjez el-Bab, Ghardimaou, Tabarka, Makthar) in the region and its most favorable bioclimatic conditions ($BIO13$, $BIO16$). These areas are the rainiest and in the extreme northwest of the region, especially the high mountains, where most of Tunisia’s forestry resources are concentrated. These areas also enjoy the highest standard of living due to their high urban connectivity and their many family networks (e.g., Ghardimaou) widely distributed in the cities and abroad. Such networks develop activities and build solidarity, which contributes to the maintenance of farms and heritage and attracts investment.

Cluster 3: These areas are characterized by an increasingly intensive production system that has enabled the development of diversified vegetable ($y_{ti\_vege}$) and fruit crops in close connection with the food industry. The system is highly labor-intensive, largely employs rural women, and is focused on cereal crops, especially in the Medjerda valley and the plains of Kef.

Cluster 4: These areas have a low population density (100 inhabitants/km$^2$) and a low standard of living. They are known as the country’s prime areas of cereal production ($y_{th\_wheat}$, $y_{ti\_wheat}$), especially the plains of Kef and Siliana. Of lesser importance are the tree crops, and there is very dynamic, intensive, and productive market gardening in the plains ($Alt\_min$) of Sers and El Ksour and Dahmani due to the development of irrigated areas.
The dominance map of each cluster highlights the most significant group of variables explaining the causal relationship between intensive agriculture and wellbeing on a local scale (10 km²) and over the whole region of northwest Tunisia (Figure 4).

Our classification using statistical tools (PLS-PM model with latent variables) shows that the wellbeing of rural communities can be characterized and mapped at the local level according to their sensitivity to the impact of agricultural intensification.

3.3. Inner Model

The inner model, linking the endogenous latent variables (LVs), highlights the negative impact of the Bioclimate variable on the Agri-intensive indicator ($\beta = -0.35$; see Table 2). This result was expected, given the increased climate risk to the yield of agricultural production in Tunisia’s Northwest region due to drought in some large cereal areas, such as Siliana and Elkef. In addition, the inner model shows other intuitive relationships, such as the significant positive correlation between Wellbeing and Demography ($\beta = 0.94$). This indicates that the factors driving rural wellbeing (schooling, healthcare, access to drinking water) are more readily available in the cities than in rural areas. The fact that the population is concentrated in the lowland areas that are more suitable for agricultural activities and,
thus, where weather conditions are favorable is reflected in the positive relationship found between the Bioclimate and Demography. Formally, these results highlight the important role of demography and suggest that demography mediates the relationship between the Agri-intensive indicator and Wellbeing. Further analysis shows that the Agri-intensive indicator has a stronger indirect effect on Demography (−0.25; see Table 2 and Appendix B).

Table 2. Total effects.

<table>
<thead>
<tr>
<th>Relationships</th>
<th>Indirect</th>
<th>Total Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bioclimate Agri-intensive</td>
<td>0.00</td>
<td>−0.35</td>
</tr>
<tr>
<td>Bioclimate Wellbeing</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>Bioclimate Demography</td>
<td>0.08</td>
<td>0.09</td>
</tr>
<tr>
<td>Agri-intensive Wellbeing</td>
<td>0.00</td>
<td>−0.26</td>
</tr>
<tr>
<td>Agri-intensive Demography</td>
<td>−0.25</td>
<td>−0.23</td>
</tr>
<tr>
<td>Wellbeing Demography</td>
<td>0.94</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Note: total effect = direct effect (inner model) + indirect effect = −0.35 + 0.00 = −0.35.

Interestingly, the results clearly show that the Agri-intensive variable has a negative impact on the wellbeing of the rural population (β = −0.26). Intensive agriculture is not known to offer rural workers attractive conditions. Farm laborers are negatively impacted by low wages, a lack of health coverage, and a reduced employment rate due to the increasing sophistication of machines. The negative net migration recorded in northwestern Tunisia can be explained by changing agricultural structures, particularly in the Medjerda Valley and the Kef Plains, where there is a strong emphasis on ownership and more capital-intensive production systems (irrigation infrastructure and rapid mechanization) [68]. According to the 2014 census, only 5 municipalities in the Northwest region had positive net population growth, while the remaining 35 municipalities experienced a net population deficit.

The tests of the overall significance validate the predictive power of the endogenous constructs (Table 3). The commonality indicates how much of the variability in the block is reproducible by the latent variable. The contribution in terms of the $R^2$ index is mainly due to the demographic effect (0.69). As a consequence, the population effect tends to obscure other weak signals’ dynamics. The redundancy index, used to measure the quality of the structural model for each endogenous latent variable, takes into account the measurement model. High redundancy means great predictability. In our study, the average wellbeing redundancy represents the fact that the Bioclimate, Agri-intensive, and Demography indicators predicted 64% of the variability in the Wellbeing indicator. This type of statistical analysis measures how much greater the variance in an estimated coefficient is in the presence of collinearity. The collinearity assessment means of the VIF yielded values between 1.07 and 7.14, which is well below the threshold value of 10 and facilitates the interpretation of the PLS-PM results.

Table 3. Summary of the Structural Model Indices.

<table>
<thead>
<tr>
<th>Type</th>
<th>$R^2$</th>
<th>Commonality</th>
<th>Redundancy</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bioclimate</td>
<td>0</td>
<td>0.61</td>
<td>0.00</td>
<td>1</td>
</tr>
<tr>
<td>Agrintensive</td>
<td>0.12</td>
<td>0.17</td>
<td>0.02</td>
<td>1.14</td>
</tr>
<tr>
<td>Wellbeing</td>
<td>0.06</td>
<td>0.69</td>
<td>0.04</td>
<td>1.07</td>
</tr>
<tr>
<td>Demography</td>
<td>0.86</td>
<td>0.69</td>
<td>0.64</td>
<td>7.14</td>
</tr>
</tbody>
</table>

Note: $R^2 \leq 0.3$ low, $0.3 < R^2 < 0.6$ moderate and $R^2 \geq 0.6$ high.

The robustness of the model (including the measurement and structural models) was assessed by the goodness-of-fit index (GOF) at 0.46, thus showing that the quality of the fit is satisfactory in supporting the validity of the overall model.
4. Discussion and Conclusions

The structural modeling approach allowed us to treat a large number of factors driving the relationship between agricultural intensification and the rural population’s wellbeing, such as climate and demography. The results reflect the well-known relationships with the usual variables involved in agricultural dynamics, such as the bioclimate (temperature and rainfall regime). This suggests that greater attention needs to be paid to the negative impacts of climate change on agricultural production, especially on vulnerable groups living in rural areas, including smallholder farmers who use rainfed agriculture for their livelihoods [69]. In addition, our results highlight the negative effect of the bioclimate indicator on intensive agriculture, raising the issues of the introduction of crops that are more sensitive to water stress, as previously pointed out [70], and of sustainability. This is especially relevant given the current climate change trend and from a food insecurity perspective [63,71,72].

More interestingly and centrally, for us, our results also highlight the negative effect of agricultural intensification on rural wellbeing. This goes beyond the income of the farmers practicing intensive agriculture. Indeed, the trend towards intensification is a major source of concern for rural communities in terms of wage levels, increasing unemployment rates that prompt them to migrate, or health (the use of chemical inputs). This has been highlighted by a number of studies, indicating that agricultural intensification rarely leads to concomitant positive outcomes in ecosystem services and human wellbeing [73]. It is less likely to reduce poverty where there is a high level of inequality and can exacerbate poverty or marginalize disadvantaged groups [74]. Along these same lines, Luna [75] showed that the intensification system has led to profound transformations in rural societies, for example, by challenging rural communal systems through the development of new labor-saving and individually profitable technologies, thus reinforcing the knock-on effect of rural–urban migration.

Studies in Africa show that agricultural intensification has amplified undernourishment and inequality in rural communities while benefiting large-scale farmers, urban populations, and agri-business [8,12], and that current rural development policies may inhibit investments aiming to support farmers’ incomes [9]. This is particularly true in Tunisia, with its stark inequalities in productivity and living standards between farmers, with large mechanized and subsidized farms on the one hand, and on the other, manual family farms where the techniques of the Green Revolution are inappropriate and counterproductive (pollution, debt, etc.). The consequence is rural exodus and mass unemployment. Such exploratory work paves the way for new or improved models that can be used to evaluate the rural population’s wellbeing indicators from a sub-communal perspective. Our results illustrate how wellbeing can be measured at the sub-communal level and by going beyond the monetary dimension to focus more on the social and climate dimensions that most affect the prosperity of the rural population or equitable development.

In terms of policy, these findings do not argue for the abandonment of pro-intensive policies but are rather in favor of complementary actions that will protect rural employment and health within changing agricultural systems. These measures could help to avoid the exacerbation of poverty that results from ignoring social inequalities and environmental concerns in intensification policies [8,76]. From this perspective, our methodological proposal provides a way to assess, at the local level, how public action impacts wellbeing. The Tunisian example is pertinent. People widely welcomed the government-backed agricultural transformation because it brought increased yields of certain crops, such as cereals and vegetables. However, this enhanced agricultural performance may have exacerbated existing risks (loss of rural jobs on the social side, increased chemical inputs on the environmental side, and costly agricultural equipment on the economic side). It may have also introduced new risks, as in cases where high-yielding varieties of seeds are unsuited to the forms of the crops, to the climate, or to the farming systems [77].

Using the PLS method within the framework of structural equation models to perform spatial analysis has many advantages. This spatial classification means that a spatial
analysis can be performed without carrying out costly and time-consuming field surveys. This classification enables intensive agriculture to be characterized beyond the standard variables (land size, quantity of inputs, mechanization), identifying links between irrigated and fertilized or rainfed crops and wellbeing on the sub-communal scale. In addition, when areas have an unusually high incidence of poverty, such a spatial location serves to highlight the target variables that can improve the wellbeing of rural households, especially when labor and household income are not fully mobile [78]. For instance, our results suggest that emphasis should be placed on economic development through public investment in infrastructure (e.g., targeted loans, integrated rural development projects) rather than the provision of direct consumption subsidies, for instance. Moreover, the structural form of our model means that it is adaptable to other comparable areas, taking into account their specific bioclimatic, socio-economic, demographic, and geographic features.

Our study presents some limitations, not least the inherent limitations of the PLS method itself [48]. Firstly, the measurement of formative constructs has not yet given rise to the same consensus as that regarding reflective constructs. A common criticism is that the parameter estimation can be either negative or positive. Estimates, therefore, become asymptotically correct only under the dual condition of “consistency” [79]: the size of the sample must be very large, and the same is true for the number of indicators per variable. In practice, these conditions are almost never met, which leads to a tendency to somewhat underestimate structural relationships and overestimate the contributions of indicators to the constructs (weights). Secondly, we showed in this study that intensive agriculture has an overall negative impact on the wellbeing of rural communities. However, this general statement applies only to the rural areas selected and to the wellbeing category chosen here. The results might be different in other locations and given other value systems, cultural identities, inequalities, levels of job security, health, community vitality, leisure, environmental factors, and subjective perceptions, which are important determinants of a population’s wellbeing and differ worldwide [19,20,22]. In addition, the index we chose seems to be reductive in that the local definition of wellbeing was not given much consideration in this research, which focused on the academic factors of wellbeing: health care, work, education, and access to drinking water. This focus contrasts sharply with traditional development indicators such as land, livestock, and agricultural income as priorities for wellbeing, as well as traditional practices closely linked to household-level food security. In the same way, other collective and contextual attributes such as the sense of belonging, security, community support, and environmental change, with the associated effects on food and water security, access to work, and collective services (schools, hospitals, public transport, etc.), could help researchers to accurately identify the factors that affect a community’s quality of life. The absence of some statistical data, such as individual income, which is difficult to measure in developing countries, also limits our definition of rural wellbeing. In Tunisia, there are few indications of farm income due to the absence of tax returns for most farmers [80]. A more precise definition of wellbeing is the next research challenge.

To conclude, this study illustrates the benefits and potential of using a statistical approach that is appropriate for issues involving unmeasured variables, such as the impact of agricultural intensification on rural wellbeing at the sub-national level. We believe this approach can support future rural policy making in developing countries. Our findings suggest that, while the generalization of the productivist system is appropriate in many industrial countries, freeing the labor force for allocation to other economic sectors, it is inappropriate in developing economies [81], where employment in the secondary and tertiary sectors is insufficient to absorb rural migrations. In these situations, agricultural intensification risks increasing yields while generating territorial poverty and emigration and increasing social wellbeing disparities in the production areas.
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**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Conflicts of Interest:** The authors declare no conflict of interest.

**Appendix A**

![Correlation Matrices of Candidate Manifest Variables of the Latent Variables.](image)

**Figure A1.** Correlation Matrices of Candidate Manifest Variables of the Latent Variables.
Appendix B

Figure A2. Total Effects (Direct and Indirect).

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