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# Examining the Spatial Effect of "Smartness" on the Relationship between Agriculture and Regional Development: The Case of Greece

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**Abstract:** Digital transformation in farming via smart farming technologies (SFTs) is highly considered to stimulate sustainability in the food market and agriculture, as well as to promote viability in the agricultural sector and the prosperity of rural areas. In Greece, a great number of SFTs were financed through Action 4.1.1, by the EU's Rural Development Program, supporting agricultural production and promoting sustainable regional development. Within this policy context, this paper aims to examine the transformation level that "smartness" induced in the relationship between agriculture and regional development in Greece. To do so, it builds a multilevel methodological framework thematically describing both "traditional" and smart agriculture in terms of spatial demand, transportation cost, knowledge intensity, and economies of scale, which are theoretically and empirically considered as major pillars related to regional development. The analysis is applied regional data (NUTS 3) in Greece, focusing on the detection of significant spatial and functional changes in the thematic model developed with respect to the proposed methodological framework. Findings provide insights into the effect that the SFTs can have on sustainable regional development, based on the reasoning of relevant background regional economic theories.

**Keywords:** smart farming; spatial demand; transportation costs; knowledge economy; economies of scale; sustainable rural development



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## 1. Introduction

Farming, animal breeding, and so-called food production are evolving through time (from Neolithic Age to nowadays) as mutually involved with technical transitions, innovations, social recreations, and turning points in history that induced social and economic theories [1]. Starting from the domestication of animals and plants, with mechanical ingenuity and rudimentary breeding skills, and moving to Industrial Revolution, with the appliance of more advanced machinery, and the green revolution of the 20th century that introduced chemical inputs and hybrid seeds, it can be said that the farmers set the bases for urban civilization by providing a surplus of food [2,3]. In the 21st century, scientific inventions (as an ongoing process) led the agricultural sector to smart farming (SF), a practice involving site-specific interventions and digital tools [4–6]. By embedding precision agriculture equipment (geo-positioning systems, decision support systems, aerial and satellite images), automations (sensors and actuators), robotics (unmanned aerial or ground vehicle), farm management information systems (FMISs), the Internet of Things (IoT), Big Data, etc., SF has become a more precise and resource-efficient approach to farming operations, therefore equipped by the potential to deliver a more productive and sustainable agricultural product [7–10].

As an innovation, SF is a source of competitive advantage, so it is also a tool for policymakers to apply new policies to address regional inequalities and divergence [11,12], supporting the point of view of Schumpeter (1990), who noted that the economy in capitalistic systems evolves and constantly changes from innovative processes or practices [13,14]. In the long run of human economic development, insights into sociocultural evolution, scientific and technical change, and ongoing economic growth formed several economic theories, mainly regional, that developed a theoretical frame which described the connection between innovation and growth. For instance, Adam Smith (1776) [15], described (at the rising of the Industrial Revolution period) in his book "An Inquiry into the Nature and Causes of the Wealth of Nations" that economic growth is attributed to firms' ability to exploit production coefficients at large scales. Smith conceived that labor division and specialization are key factors for enlarging revenue and driving economies of scale through the emergence of production with minimized input cost. According to his theory, agriculture (depending on the area of the land, where 70% of the owners of production are smallholder farmers) is less amenable to the diversification of labor than the manufacturing sector; this is a key factor for not achieving a reduction in inputs in this sector of the economy [16]. A further approach to interpreting economic growth in terms of labor specialization was the comparative advantage theory, presented by David Ricardo (*On the Principles of Political Economy and Taxation*, 1817), stating that economic growth can be reached when countries produce goods at lower opportunity costs through specializing [17]. A modern view in the standard Ricardian models argues that there is a two-way relationship between trade and technology since trade affects the direction of innovation through its impact on the expected market size for an invention [18,19]. Moreover, in the context of the endogenous development theory as introduced by Romer (1986) [20] and Lucas (1988) [21], regional growth and development are conceived as a self-propelling process stimulated by knowledge acquisition and learning local engines, which attributes the production mechanism of a regional economy to an increasing return scale, causes positive externalities and spillover effects, and leads to knowledge-based regional and economic development [22]. In this context, when an agricultural region is located close to an industrial one, although it becomes a less prospective factor to be engaged in the innovation process, it ultimately benefits from the knowledge accumulation nearby through an engine of local spillovers [23].

In terms of spatial concentration, Marshal (1879) [24] argued that despite the growing importance of internal economies of scale and the resultant effects on the size distribution of firms (towards large firms), it was still possible for agglomerations of small firms to be efficient and to compete with larger firms on an equal footing [25]. By focusing on the role of local knowledge spillovers, the existence of non-traded local inputs, and a local specialist labor pool forming localization economies, he contributed to comprehending the engine of economic growth in the context of proximity. According to Marshal, urbanization and localization economies are two major forms of agglomeration, where neighborhood firms benefit in productivity, business concentration, and resource efficiency, provided they are not dependent on one industry for their economic development. Compared with other industries, agriculture is highly affected by social agglomeration factors, such as historical traditions, land tenure, ownership patterns, institutions, culture, and regulation, where unique agglomeration patterns and mechanisms emerge, such as biological characteristics and great dependence on inter-related natural conditions of climate, elevation, drainage, and soil suitability [17,26]. Further, other theories of regional development highlight the importance of geography and geographical distance for stimulating the engine of regional and economic development. For instance, in the context of the resource base theory [27], regional inequalities are conceived as a result of the uneven geographical distribution of resources, which causes differential accessibility to the production coefficients for places and thus consequent inequalities in their growth rates and developmental dynamics. In the context of the new economic geography (NEG) [28,29], accessibility becomes the main factor for regional economic growth, developing core–periphery patterns based on transportation costs. For instance, regional economies submitted to low transportation costs develop centripetal forces leading to agglomeration and development of central places, whereas those submitted to high transportation costs develop centrifugal forces leading to peripheralization and development of peripheral markets [30,31].

The previous brief review allows observing that, in the recent past centuries of economic research [15,20,21,24,27,28,30], regional economic growth and development are conceived through the main pillars of scale effects (economies of scale), specialization, spatial agglomeration, geographical allocation of resources, knowledge multiplication effect and innovation (knowledge-based economies), and transportation costs, where the sustainability requirement applies incorporating environmental and social welfare. Within this theoretical context, SF is experienced as a force shifting the traditional economic balance of regional economies into a new state of functionality. Such a shift, the transition towards "smartness", suggests a transformation building on the current aspect of innovation related to digitization and communication, commonly known as the digital transformation of the economy [32]. Therefore, according to Roger's diffusion of innovation social science theory [33], the agricultural sector currently steps into the chasm (Figure 1) between the early and mainstream market, as smartness applies to the traditional economic balance and defragments the dynamics of regional economies towards new states of sustainable regional and economic development.

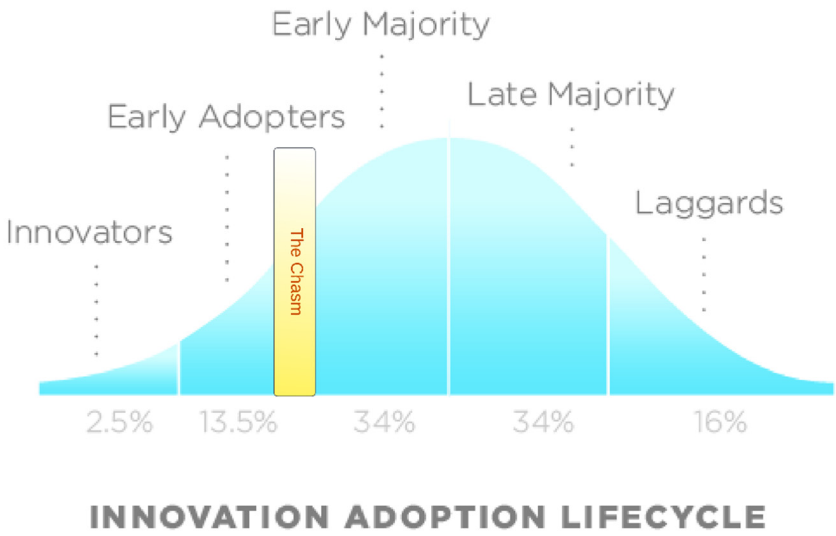



**Figure 1.** A tech innovation curve according to Roger's diffusion of innovation social science theory [33] (own elaboration with Lusidchart -Lusid Software Inc., Salt Lake City, UT, USA, https://lucid.app/lucidchart-Original (accessed on 2 February 2023) picture used under the Creative Commons Attribution-Share Alike 3.0 Unported license from https://commons.wikimedia.org/wiki/File:DiffusionOfInnovation.png Created by Creative Commons Attribution 2.5 Generic, accessed on 10 February 2023).

Within this context, this paper aims to revisit the drivers of sustainable regional economic development due to the digital transformation ("smartness") that currently applies to the global economy. To do so, it builds on the theoretical legacy that theories of regional economics and development configured, and it aims to quantitatively capture the digital transformation (shift) that SF is about to apply to the agricultural sector. In technical terms, this is done by constructing a system of multiplex regression models, consisting of the same predictors and different response variables, where the predictors represent aspects of the (theoretically known) drivers of regional economic development, as extracted from the previous literature review, whereas the dependent variables represent aspects of "traditional" (conventional) and "smart" agriculture. Within the legacy that theories of regional economics and development provide and based on the principles of sustainable development, we aim to forecast the evolution and growth that SF is expected to have based on the differences captured by the model coefficients. Overall, this paper contributes to locating patterns of the geographical distribution of the current agricultural holdings that are willing to invest in SF, therefore clarifying the acceptance of usefulness in Greece. Moreover, the revealed spatial distribution of the non-adopters in relation to the response variables of the theoretical frame could assist policymakers in designing interventions through aid schemes for adaptation of smart farming technologies (SFTs) and abbreviate the "chasm". Combining three methodological frames, an effort is made to reply to the main research question: "Are SFTs capable of reconstructing rural areas and advocating sustainability, or is their diffusion prolonged and relevantly dispersed in the known development patterns, as in traditional agriculture, towards economic growth?" In related literature [34–38], in the past few years, there has been no concurrency on a standardized method or concept that assesses agricultural systems' sustainability on a large scale in a region or a country. Generally, multicriteria methods are applied in indicator-based tools, frameworks, and indexes, in farm-level case studies that focus on resource use [39].

The remainder of this paper is organized as follows: in Section 2, there is a detailed presentation of the method followed and the data used; in Section 3, the results of the analyses (hot spot, kernel density, and BEM) are demonstrated; and in Section 4, the essential features of the results are discussed.

## 2. Materials and Methods

This study develops a multilevel methodological framework capturing changes in agriculture due to the digital transformation of the sector. The data used were provided by the Hellenic's Republic Ministry of Rural Development & Food Unit of Investments in Agricultural Holdings under the Implementing Authority for Rural Development Program, a special unit that manages the rural development programs (RDPs) of the European Union's "European Agricultural Fund for Rural Development" (EAFRD). In the period from 2019 to 2022, the fund financed a total of 14,748 innovative investments of agricultural holdings in Greece, in order to improve the competitiveness of agriculture. A number of 4013 investments were innovative in SFTs and were subsidized through the 2nd call of Action 4.1.1 "Implementation of investments that contribute to farm competitiveness" (Table 1), guiding the path towards Agriculture 4.0. Primary data of the 1276 holdings originated from the Unitary Application for Aid Schemes (UASS) of the year 2018, and the 4013 investments issued from Action 4.1.1 were used to form three dependent values, one for each model within level 3 of Nomenclature of Territorial Units for Statistics (NUTS III). The size of the data is highly considerable, and the methodologies used are divergent.

**Table 1.** Subsidization categories according to the Action 4.1.1 (Implementation of investments that contribute to farm competitiveness) (own elaboration).

| Category [1] | Subcategory [1] | Name of Category |
|---|---|---|
| 1 | 11–16 | GPS Vehicle Guidance |
| 2 | 21–28 | Farm Management Information Systems |
| 3 | 36–39 & 311–312 & 320 | Plant production facility equipment |
| 4 | 48–49 & 410–415 | Variable Rate Crop Spraying Systems |
| 5 | 531 & 533 | Variable Rate Applicators |

[1] Categories/Subcategories of investments eligible for Aid Schemes.

Data were divided into two data sets, one coming from the application of the beneficiaries for Action 4.1.1 and the other from their UASS 2018; thus, after accumulating each one into sets per NUTS 3 (georeferenced), univariate descriptive statistics were applied for the number of beneficiaries and investments and the cost of investments. Out of 52 NUTS 3 units in Greek territory, holdings from 49 of them were financed. The analysis builds on a system of three thematic regression models capturing diverse aspects of agriculture: income and private and public investments in agriculture, as shown in Figure 2. All three models consist of the same number of predictors representing pillars of sustainable regional and economic development. This structure of similarity, across the predictor modes, provides properties of multiplexity in the structure of the total model. In particular, the sixteen predictor variables of the model are extracted from the relevant literature [15,20,21,24,27,28,30], based on the previous brief review, trying to quantify different factors that are theoretically known as drivers stimulating regional growth and development. The selection was made as an attempt to focus on the high relevance of their influence on technical innovation in agriculture in general and more specifically to determine the importance of each in the adoption of smart farming technologies (SFTs) in the case of Greece.

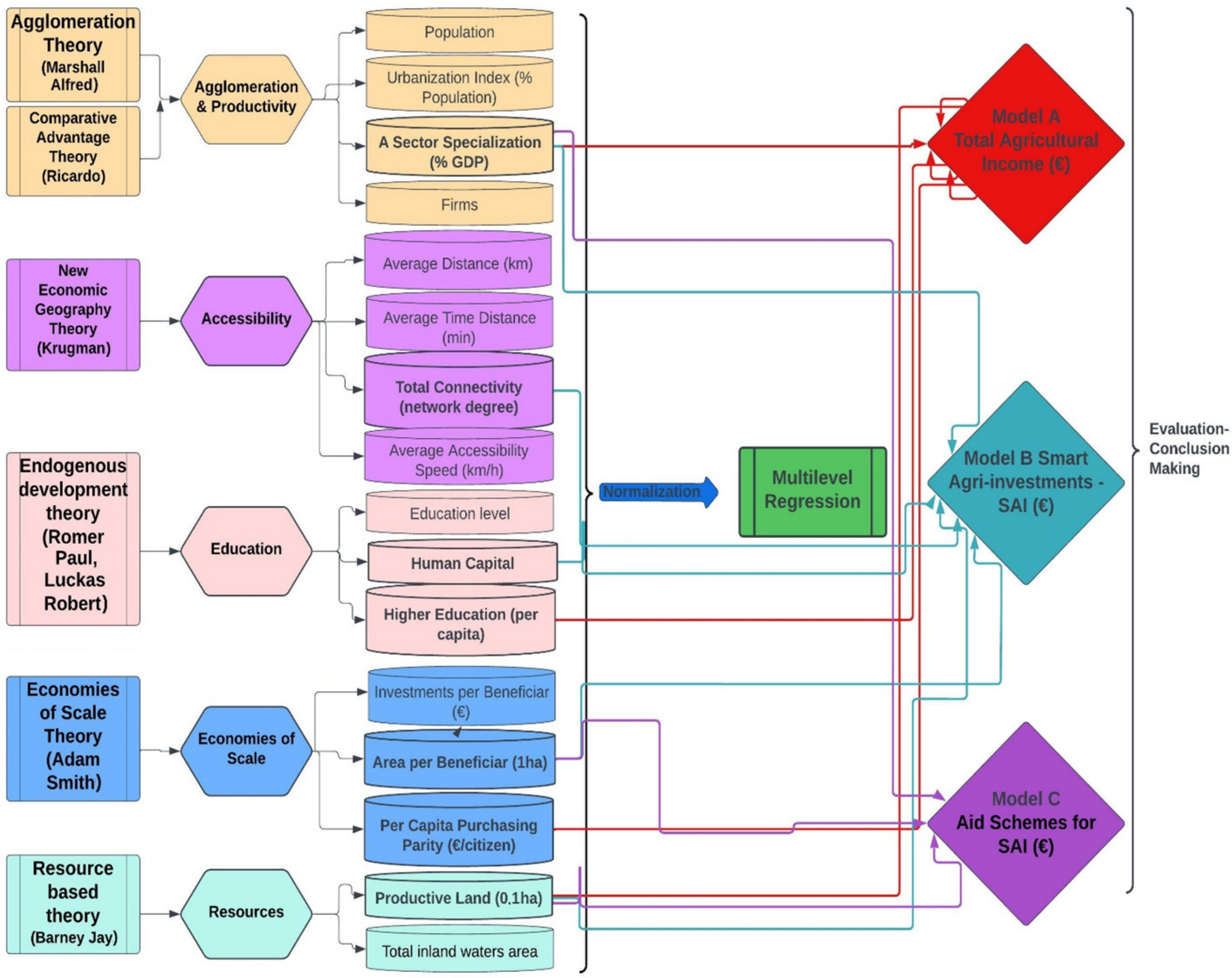



**Figure 2.** Flow chart showing the methodological framework of the study designed with Lusidchart own elaboration (Lusid Software Inc., Salt Lake City, UT, USA, https://lucid.app/lucidchart/ (accessed on 2 February 2023)).

Each theory states key features and prominent parts of the social and economic development process and, based on the available literature [40–43], aggregates a great number of socioeconomic indexes. Within this context, the available predictor variables included in the analysis are shown in Table 2. Agglomeration theory and comparative advantage theory are represented by four indexes that describe population, firm concentration, and specialization; endogenous development theory is represented by three factors that define knowledge obtainment; economies of scale are represented by another three factors that conceptualize diversification of labor and capital investment; NEG theory is specified by four accessibility-driven vectors; and resource base theory is specified by another two agricultural asset-driven factors.

**Table 2.** The available variables participating in the analysis, grouped in accordance with their thematic relevance.

| Theoretical Context | Representatives | Code | Description | Source |
|---|---|---|---|---|
| Agglomeration Theory and Comparative Advantage Theory | Population | ×1.1 | The population of each prefecture (NUTS III), according to the 2011 national census. | [40] |
| | Urbanization Index (% Population) | ×1.2 | Defined by the share of a prefecture's capital city to the prefecture's population. | [41] |
| | A Sector Specialization (% GDP) | ×1.3 | The share of % GDP attributed to agriculture (primary sector). | [42] |
| | Firms | ×1.4 | The number of firms registered in each prefecture. | [40] |
| New Economic Geography Theory | Average Distance (km) | ×2.1 | The average kilometric distance of each prefecture to the others. | [43] |
| | Average Time Distance (min) | ×2.2 | The average time distance (measured in minutes) of each prefecture to the others. | [43] |
| | Total Connectivity (network degree) | ×2.3 | Composite index measuring the aggregated average degree of multimodal transportation networks of Greek prefectures. | [43] |
| | Average Accessibility Speed (km/h) | ×2.4 | The average speed (km/h) required to access a prefecture. | [43] |
| Endogenous Development Theory | Education level | ×3.1 | Composite index measuring the level of Education in a prefecture. | [40] |
| | Human Capital | ×3.2 | Composite index measuring the level of education of labor force (labor production coefficient) in a prefecture. | [40] |
| | Higher Education (per capita) | ×3.3 | A number showing the population corresponding to one person with higher education (per capita) | [40] |
| Economies of Scale Theory | Investments per Beneficiary (€) | ×4.1 | The total budget of investments corresponding to a beneficiary (€), per prefecture. | Aggregated from data |
| | Area per Beneficiary (1 ha) | ×4.2 | The total area corresponding to a beneficiary (1 ha), per prefecture. | Aggregated from data |
| | Per Capita Purchasing Parity (€/citizen) | ×4.3 | The per capita purchasing parity (€/citizen) of a prefecture | [40] |
| Resource Base Theory | Productive land (0.1 ha) | ×5.1 | The total productive land area, per prefecture (0.1 ha). | [40] |
| | Total inland waters area | ×5.2 | The total inland waters area, per prefecture. | [40] |

Next, we construct a system of three linear regression models describing total agricultural income (TAI), smart agricultural investments (SAIs), and aid schemes for SAI in Greece as a function of the variables shown in Table 2. In particular, on the same set of available predictors (independent) variables $X = \{\mathbf{x}_{1.1}, \mathbf{x}_{1.2}, \mathbf{x}_{1.3}, \mathbf{x}_{1.4}, \mathbf{x}_{2.1}, \mathbf{x}_{2.2}, \mathbf{x}_{2.3}, \mathbf{x}_{2.4}, \mathbf{x}_{3.1}, \mathbf{x}_{3.2}, \mathbf{x}_{3.3}, \mathbf{x}_{4.1}, \mathbf{x}_{4.2}, \mathbf{x}_{4.3}, \mathbf{x}_{5.1}, \mathbf{x}_{5.2}\}$, we develop three multivariate regression models, as follows:

Model A (total agricultural income (TAI)): The first model describes the total agricultural income in Greece ≡ TAI ≡ $\boldsymbol{y}_A$ as a function of the available predictor (independent) variables $X$ shown in Table 2, according to the expression $\boldsymbol{y}_A = f(\mathbf{x}_{1.1}, \mathbf{x}_{1.2}, \mathbf{x}_{1.3}, \mathbf{x}_{1.4}, \mathbf{x}_{2.1}, \mathbf{x}_{2.2}, \mathbf{x}_{2.3}, \mathbf{x}_{2.4}, \mathbf{x}_{3.1}, \mathbf{x}_{3.2}, \mathbf{x}_{3.3}, \mathbf{x}_{4.1}, \mathbf{x}_{4.2}, \mathbf{x}_{4.3}, \mathbf{x}_{5.1}, \mathbf{x}_{5.2})$, or for the sake of simplicity $\boldsymbol{y}_A = f(X)$. The TAI variable describes the standard income produced by all plant and animal production of beneficiaries (per NUTS 3 regional unit) that is declared in the Unitary Application for Aid Schemes (UASS) for the year 2018. Data for this predictor variable were extracted from the two datasets after accumulating each one into sets per NUTS 3.

Model B (smart agricultural investments (SAIs)): The second model describes the smart agricultural investments ≡ SAI ≡ $\boldsymbol{y}_B$ as a function of the available predictor variables $X$, according to the expression $\boldsymbol{y}_B = f(X)$. The SAI variable is defined by the total cost of purchased equipment per NUTS 3 of the investments made in the years from 2018 to 2022 in Greece. Data for this predictor variable were extracted from the dataset of the application of the beneficiaries for Action 4.1.1 after accumulating each one into sets per NUTS 3.

Model C (SAI aid schemes (SAIASs)): The third model describes the smart agricultural investments ≡ **SAIAS** ≡ $\boldsymbol{y}_C$ as a function of the available predictor variables $X$, according to the expression $\boldsymbol{y}_C = f(X)$. The SAIAS variable is defined by the sum of the number of aid schemes that were financed through the RDP in the years from 2018 to 2022 in Greece. Data for this predictor variable were extracted as for Model B.

Further, we specialize each model by using the backward elimination method (BEM) [44,45], which is an iterative process applied to a standard multivariate linear regression model by successively removing insignificant predictors. In particular, the BEM method starts with the full number of the available predictors (independent variables) $X = \{\mathbf{x}_{1.1}, \mathbf{x}_{1.2}, \mathbf{x}_{1.3}, \mathbf{x}_{1.4}, \mathbf{x}_{2.1}, \mathbf{x}_{2.2}, \mathbf{x}_{2.3}, \mathbf{x}_{2.4}, \mathbf{x}_{3.1}, \mathbf{x}_{3.2}, \mathbf{x}_{3.3}, \mathbf{x}_{4.1}, \mathbf{x}_{4.2}, \mathbf{x}_{4.3}, \mathbf{x}_{5.1}, \mathbf{x}_{5.2}\}$ and successively removes the most insignificant ones (one per loop), namely those with $p$-value (significance) greater than 10% ($p > 0.1$). In general, for a given set of predictors $X_n = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$, the sequence of the BEM models ($\boldsymbol{y}_k$), $k \geq 0$, is described as follows [46]:

$$(\mathbf{y}_k)_{k\in\{1,\ldots,n\}\subseteq\mathbb{N}}\Big|\mathbf{y}_k = \sum_{i=1}^{n-k+1} b_i \cdot \mathbf{x}_i + c_k \cdot \mathbf{1} = f_k(\mathbf{x}_i)$$
$$\begin{cases} X_n = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}, \\ \mathbf{x}_i \in X_{n-k+1}, \\ X_{n-k} = X_{n-k+1} - \{\mathbf{x}_p\} \\ \mathbf{x}_p \in X_{n-k+1} : P[b(\mathbf{x}_p) = 0] = \max\{P[b_i = 0] \geq 0.1\} \end{cases} \quad (1)$$

where $n$ is the number of predictors and $k$ is the number of iterations applied to the model. The final BEM model $\boldsymbol{y}_k$ includes only significant predictors ($p(\boldsymbol{x}_i) \leq 0.1$)). The "beta" coefficients produced by this method capture the participation (slope) of each predictor in the model [47]. In calculations, 95% confidence intervals (CIs) are considered and the missing values are excluded pairwisely, according to which maximum possible sample sizes of variables are considered from test to test. Within this context, the overall consideration of the three available models can be seen as a multiplex (multivariate) linear regression model, expressed by the following system of equations:

$$\begin{cases} \mathbf{y}_{Ak} = \delta_{A1} \cdot b_{A1} \cdot \mathbf{x}_1 + \delta_{A2} \cdot b_{A2} \cdot \mathbf{x}_2 + \ldots + \delta_{An} \cdot b_{An} \cdot \mathbf{x}_n \\ \mathbf{y}_{Bk} = \delta_{B1} \cdot b_{B1} \cdot \mathbf{x}_1 + \delta_{B2} \cdot b_{B2} \cdot \mathbf{x}_2 + \ldots + \delta_{Bn} \cdot b_{Bn} \cdot \mathbf{x}_n \\ \mathbf{y}_{Ck} = \delta_{C1} \cdot b_{C1} \cdot \mathbf{x}_1 + \delta_{C2} \cdot b_{C2} \cdot \mathbf{x}_2 + \ldots + \delta_{Cn} \cdot b_{Cn} \cdot \mathbf{x}_n \end{cases} \quad (2)$$

where $\delta_{ji}$, $j$ = A, B, C and $i$= 1, 2, ... , $n$ are the Kronecker's delta functions giving one (=1) when predictor $\boldsymbol{x}_i$ is significant, and $b_{ji}$, $j$ = A, B, C and $i$ = 1, 2, ... , $n$, are the concordant regression coefficients. This multiplex linear regression model (consisting of three components: model A, model B, and model C) allows describing different aspects of traditional and smart agriculture in Greece (TAI, SAI, SAIAS) within the same theoretical context, as captured by the set of available predictor variables $X = \{\mathbf{x}_{1.1}, \mathbf{x}_{1.2}, \mathbf{x}_{1.3}, \mathbf{x}_{1.4}, \mathbf{x}_{2.1}, \mathbf{x}_{2.2}, \mathbf{x}_{2.3}, \mathbf{x}_{2.4}, \mathbf{x}_{3.1}, \mathbf{x}_{3.2}, \mathbf{x}_{3.3}, \mathbf{x}_{4.1}, \mathbf{x}_{4.2}, \mathbf{x}_{4.3}, \mathbf{x}_{5.1}, \mathbf{x}_{5.2}\}$. To the extent that $X$ is theoretically conceived by the underlying theories of regional development shown in Figure 2, comparisons between the available models (components) may provide insights into the developmental dynamics of "traditional" and "smart" farming in Greece, as expressed by the total agricultural income (TAI), smart agricultural investment (SAI), and SAI aid scheme (SAIAS) predictor variables.

To further analyze the spatial dynamics of the available predictor variables, a hot spot spatial pattern analysis was conducted for the sum of investments made per NUTS 3 using Environmental Systems Research Institute (ESRI) ArcGIS Desktop 10.5; this is an analysis and mapping technique operation for the identification of clustering of spatial phenomena depicted as points in a map and refers to locations of events or objects using the Getis–Ord $G_i$* algorithm (Equations (3)–(5)). A hot spot can be defined as an area that has a higher concentration of events compared to the expected number given a random distribution of events. The tool identified statistically significant clusters of a high quantity (hot spots) and a low quantity (cold spots) by looking at each water supply zone within the context of the neighboring zones (i.e., NUTS 3). The Getis–Ord local statistic is given as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \overline{X} \cdot \sum_{j=1}^{n} w_{ij}}{s \cdot \sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \tag{3}$$

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{4}$$

$$s = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X}\right)^2} \tag{5}$$

where $x_j$ is the attribute value (i.e., cost of investments made) for NUTS 3 zone $j$, $w_{ij}$ is the spatial weight between zone $i$ and $j$, $n$ is equal to the total number of observations (total 49), $\overline{X}$ = mean of the cost of investments for zone $j$, and $S$ = standard deviation of the cost of investments. The $G_i$* statistic is a z-score for each NUTS 3 zone. The statistically significant positive z-scores with larger z-score represent more intense clustering of high values (hot spot), and statistically significant negative z-scores with a smaller z-score represent more intense clustering of low values (cold spots) [48]. Beyond assessing the density of points in a given area, hot spot techniques also measure the extent of point event interaction to understand spatial patterns.

In order to demonstrate a directional trend in the spatial distribution of the number of investments made, kernel density estimation was performed. Kernel density is a non-parametric method for estimating probability density function [49]. The smooth peak function fits the observed data points to simulate the actual probability distribution curve, so the kernel function is a smooth-conversion and weighted function. We used the kernel density tool of ESRI ArcGIS PRO 3.0 which calculates the density of features in a neighborhood around those features. After point features (NUTS 3) are entered into the tool and the population of a field (number of investments made) is selected, it extracts a raster layer after weighting fields' features more heavily than others. The extraction (floating point raster layer) calculates the density of point features around each output raster cell by fitting a smoothly curved surface over each point. The volume under the surface equals the population field value for the point, so the surface value is highest at the location of the point and diminishes with increasing distance from the point, reaching zero at the search radius distance from the point. The density at each output raster cell is calculated by adding the values of all the kernel surfaces where they overlay the raster cell center. The kernel function is based on the quartic kernel function described by Silverman [50], where the predicted density at a point ($x$,$y$) location is determined by

$$density = \frac{1}{(radius)^2} \cdot \sum_{i=1}^{n} \left[\frac{3}{\pi} \cdot pop_i \cdot \left(1 - \left(\frac{dist_i}{radius}\right)^2\right)^2\right] \tag{6}$$
$$for\ dist_i < radius$$

where the $i = 1, \ldots, n$ are the input points, $pop_i$ is the population field value of point $i$, and $dist_i$ is the distance between point $i$ and the ($x$,$y$) location. Since the population field is provided, the calculated density is multiplied by the sum of the population so that the spatial integral equals the sum of the population field. The calculations are applied to the center of every cell in the output raster.

## 3. Results and Discussion

### *3.1. Spatial Patterns of Models' Response Variables*

In the cumulative data of Action's 4.1.1 "Implementation of investments that contribute to farm competitiveness" program for rural development in Greece of all 4013 investments made (Figure 3) of a sum of 1276 agricultural holdings in 49 units of 52 NUTS 3 units (Figure 4a), there is a conspicuous trend that the majority of them are located in regions with tradition in agriculture, mostly arable land and permanent plantations, large plains (Figure 4b), areas with good access to the road network (Figure 4d), and areas of ecological interest (NATURA 2000 network, zones vulnerable to nitrates of agricultural origin, etc.) (Figure 4c).

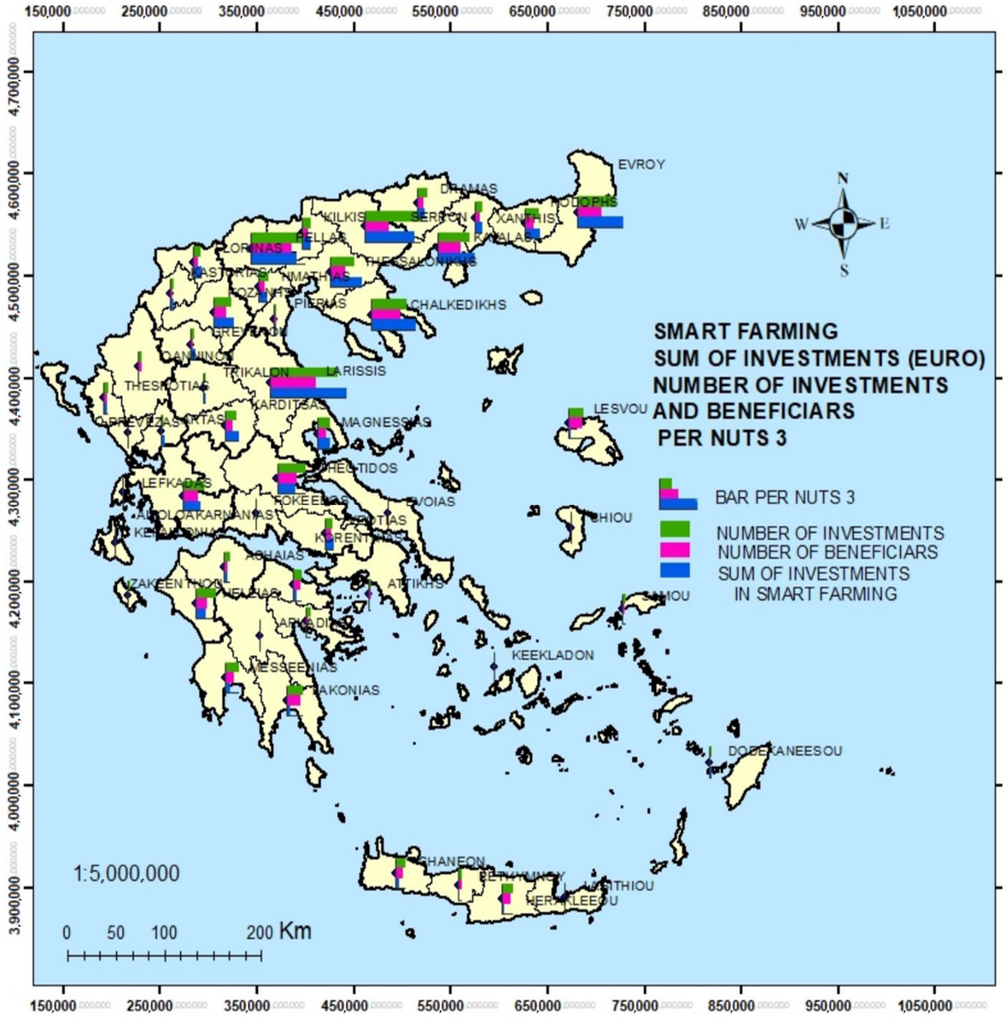
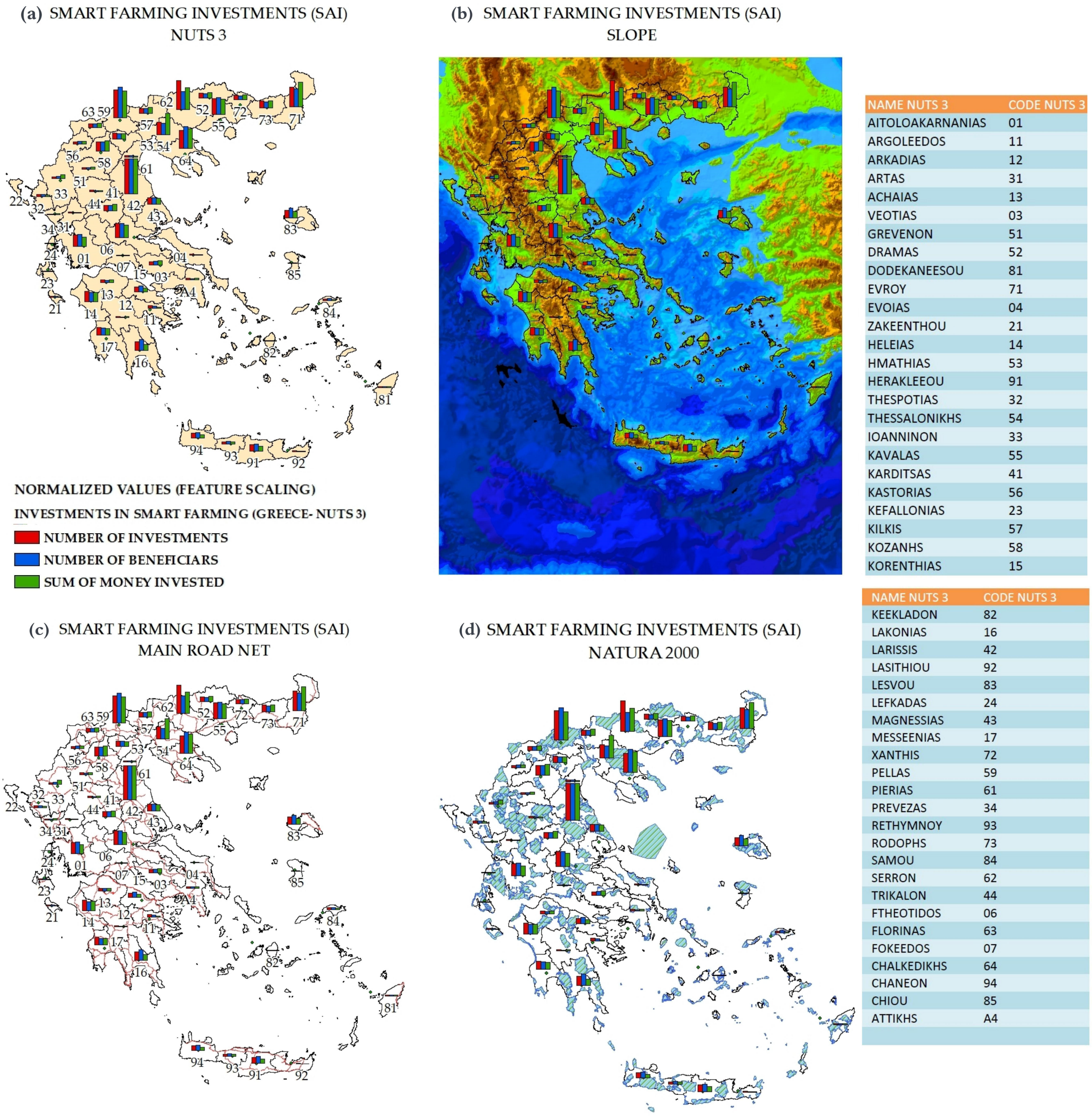



**Figure 3.** Spatial distribution of SF investments (SFIs) in Greece (normalization of values by feature scaling, depicted own elaboration in ESRI ArcGIS Desktop 10.5-ESRI 2016. ArcGIS Desktop: Release 10.5, Redlands, CA: Environmental Systems Research Institute).




| NAME NUTS 3 | CODE NUTS 3 |
|---|---|
| AITOLOAKARNANIAS | 01 |
| ARGOLEEDOS | 11 |
| ARKADIAS | 12 |
| ARTAS | 31 |
| ACHAIAS | 13 |
| VEOTIAS | 03 |
| GREVENON | 51 |
| DRAMAS | 52 |
| DODEKANEESOU | 81 |
| EVROY | 71 |
| EVOIAS | 04 |
| ZAKEENTHOU | 21 |
| HELEIAS | 14 |
| HMATHIAS | 53 |
| HERAKLEEOU | 91 |
| THESPOTIAS | 32 |
| THESSALONIKHS | 54 |
| IOANNINON | 33 |
| KAVALAS | 55 |
| KARDITSAS | 41 |
| KASTORIAS | 56 |
| KEFALLONIAS | 23 |
| KILKIS | 57 |
| KOZANHS | 58 |
| KORENTHIAS | 15 |
| KEEKLADON | 82 |
| LAKONIAS | 16 |
| LARISSIS | 42 |
| LASITHIOU | 92 |
| LESVOU | 83 |
| LEFKADAS | 24 |
| MAGNESSIAS | 43 |
| MESSEENIAS | 17 |
| XANTHIS | 72 |
| PELLAS | 59 |
| PIERIAS | 61 |
| PREVEZAS | 34 |
| RETHYMNOY | 93 |
| RODOPHS | 73 |
| SAMOU | 84 |
| SERRON | 62 |
| TRIKALON | 44 |
| FTHEOTIDOS | 06 |
| FLORINAS | 63 |
| FOKEEDOS | 07 |
| CHALKEDIKHS | 64 |
| CHANEON | 94 |
| CHIOU | 85 |
| ATTIKHS | A4 |

**Figure 4.** Bar charts of the investments made (normalization of values by feature scaling, designed own elaboration in ESRI ArcGIS Desktop 10.5 (ESRI 2016. ArcGIS Desktop: Release 10.5, Redlands, CA: Environmental Systems Research Institute), and depicted with Lusidchart own elaboration (Lucid Software Inc., Salt Lake City, UT, USA, https://lucid.app/lucidchart/ (accessed on 2 February 2023))).

For a further interpretation of the sum of investments (per NUTS 3) made, we applied hot spot analysis in ESRI ArcGIS Desktop 10.5 to detect spatial clusters and probably reveal any pattern that can explain the distribution of the values entered (Figure 5). The tool identified statistically significant clusters of a high quantity of cost of investments (hot spots) gathered in Central and East Macedonia regions; thus, there is a spatial clustering of high values of Z-score and low p-value given a random distribution. In these regions, there is also a high cluster of firms and schools with continuous scientific work [51] and many innovators in smart and precision farming (the predecessor of smart farming) [52]. To succeed, decision makers could benefit from accessible information not just about specific locations of provable innovative investments in SFTs, but also about broader trends in these data that can be detected early enough to influence a new trajectory.

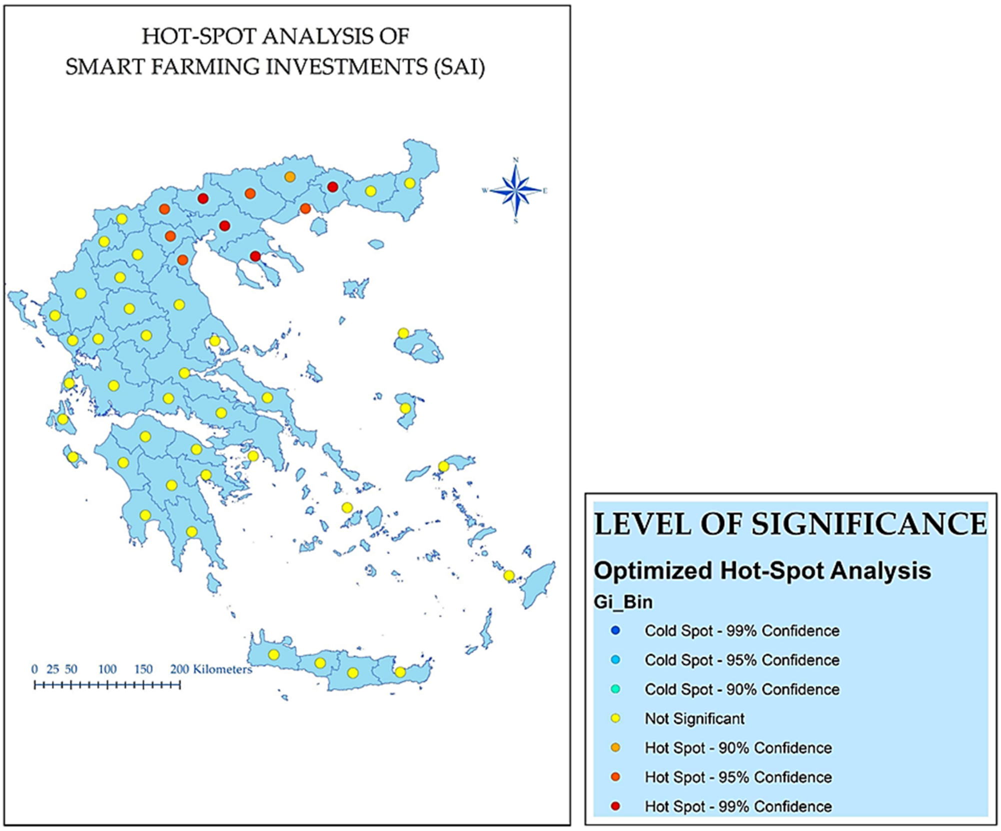



**Figure 5.** Hot spot analysis of SAI (depicted in ESRI ArcGIS Desktop 10.5-ESRI 2016. ArcGIS Desktop: Release 10.5, Redlands, CA: Environmental Systems Research Institute).

In addition, by using kernel density estimation (KDE) in ESRI Arc-Map PRO, which calculates the density of features in a neighborhood around the features, another pattern is revealed, the possibility of diffusion of the innovative investments (Figure 6). Kernel density estimation (KDE) is a common approach to explanatory spatial point pattern analysis [53]. It can estimate a continuous probability density surface of the point event over geographic space based on a set of discrete sample event locations [54]. The density surface can be used to detect and visualize event hot spots (i.e., clusters) to facilitate qualitative investigation of the point pattern [49]; in our case, most innovative investments are allocated along an S-type direction that complies with the pattern defining regional development in Greece for several years. The edge regions are laggards, and the regions highly connected and interconnected by road networks are favored [40,41,55]. Another view discusses the co-existence of two development models, namely the growth poles and the integrated endogenous development model, that eventually act supplementary to each other [56]. Either way, as expressed by Roggers [33], by definition, innovation, communication channels, time, and social system are the four key components of the diffusion of innovations, so proximity and connectivity (as in sociology), visualized in Figure 6, are predicted to be promising for SF.

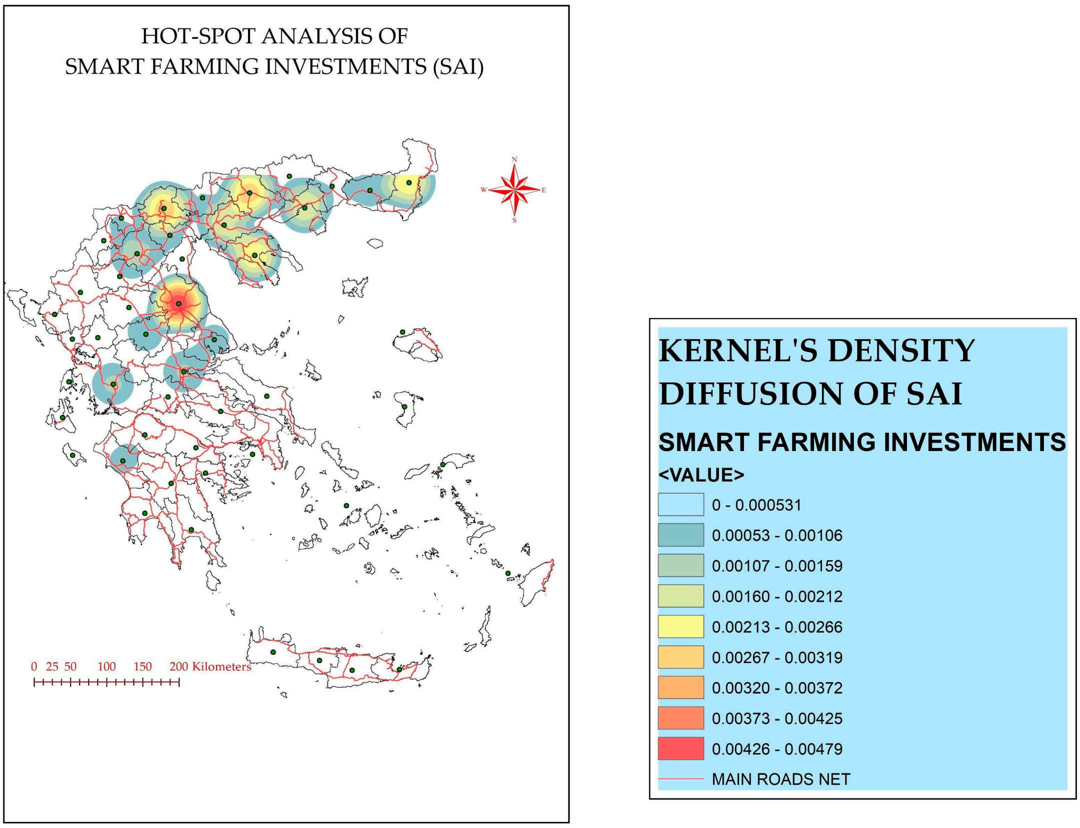



**Figure 6.** Probability of diffusion of SAI using kernel density (designed own elaboration in ESRI ArcGIS PRO and depicted own elaboration in ESRI ArcGIS Desktop).

*3.2. Econometric Modeling*

The results of the analysis are shown in Table 3 and are organized into two sub-tables per model. The first sub-table includes model summary information, describing the dependent (response) variable and the level of the model's determination ($R^2$ metrics), whereas the second sub-table provides information about the model (non-standardized and standardized) coefficients and their significance. In all models, the analysis started including the same number of predictors (shown in Table 2) but kept only the significant ($p > 0.1$) dependent variables shown in Table 3. For a better supervision of the results of Table 3, we created a brace map of the significant variables in each model and a clustered bar visualizing the standardized coefficients, as shown in Figure 7.

**Table 3.** Results of the backward elimination method (BEM) linear regression analysis.

| **Model A** | **Model Summary** | | | | **Coefficients** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: Total Agricultural Income (EUR) | $R$ | $R^2$ | $R^2$Adj | Std. Error of the Estimate | Unstandardized Coefficients | | Standardized Coefficients | | | 95% Confidence Interval for B | |
| | 0.732 | 0.536 | 0.496 | *0.170159* | *B* | *Std. Error* | Beta | t | Sig. | Lower Bound | Upper Bound |
| Independent Variables | Constant | | | | −0.149 | 0.094 | | −1.591 | 0.118 | −0.337 | 0.039 |
| | A Sector Specialization (% GDP) | | | | 0.394 | 0.128 | 0.394 | 3.072 | 0.004 | 0.136 | 0.652 |
| | Higher Education (per capita) | | | | 0.330 | 0.169 | 0.255 | 1.954 | 0.057 | −0.010 | 0.670 |
| | Per Capita Purchasing Parity (EUR/citizen) | | | | −0.232 | 0.121 | −0.218 | −1.921 | 0.061 | −0.474 | 0.011 |
| | Productive Land (1 ha) | | | | 0.599 | 0.110 | 0.543 | 5.098 | 0.000 | 0.338 | 0.779 |
| Model B | **Model Summary** | | | | **Coefficients** | | | | | | |
| Dependent Variable: Smart Farming Investments—SFI (EUR) | $R$ | $R^2$ | $R^2$Adj | Std. Error of the Estimate | Unstandardized Coefficients | | Standardized Coefficients | | | 95% Confidence Interval for B | |
| | 0.869 | 0.755 | 0.728 | *0.1118427* | *B* | *Std. Error* | Beta | t | Sig. | Lower Bound | Upper Bound |
| Independent Variables | Constant | | | | −0.023 | 0.050 | | −0.461 | 0.647 | −0.124 | 0.078 |
| | A Sector Specialization (% GDP) | | | | 0.238 | 0.084 | 0.265 | 2.827 | 0.007 | 0.068 | 0.407 |
| | Total Connectivity (network degree) | | | | −0.324 | 0.192 | −0.244 | −1.685 | 0.099 | −0.712 | 0.063 |
| | Human Capital | | | | 0.402 | 0.214 | 0.288 | 1.878 | 0.067 | −0.029 | 0.834 |
| | Area per Beneficiary (1 ha) | | | | −0.287 | 0.104 | −0.243 | −2.756 | 0.008 | −0.496 | −0.077 |
| | Productive Land (1 ha) | | | | 0.776 | 0.076 | 0.843 | 10.196 | 0.000 | 0.623 | 0.929 |
| Model C | **Model Summary** | | | | **Coefficients** | | | | | | |
| Dependent Variable: RDP Investments Aid Schemes for SF (EUR) | $R$ | $R^2$ | $R^2$Adj | Std. Error of the Estimate | Unstandardized Coefficients | | Standardized Coefficients | | | 95% Confidence Interval for B | |
| | 0.853 | 0.728 | 0.711 | *0.1125364* | *B* | *Std. Error* | Beta | t | Sig. | Lower Bound | Upper Bound |
| Independent Variables | Constant | | | | −0.037 | 0.040 | | −0.924 | 0.360 | −0.116 | 0.043 |
| | A Sector Specialization (% GDP) | | | | 0.158 | 0.070 | 0.181 | 2.256 | 0.029 | 0.029 | 0.299 |
| | Area per Beneficiary (1 ha) | | | | −0.209 | 0.095 | −0.182 | −2.206 | 0.032 | 0.032 | −0.018 |
| | Productive land (1 ha) | | | | 0.755 | 0.074 | 0.840 | 10.232 | 0.000 | 0.000 | 0.903 |

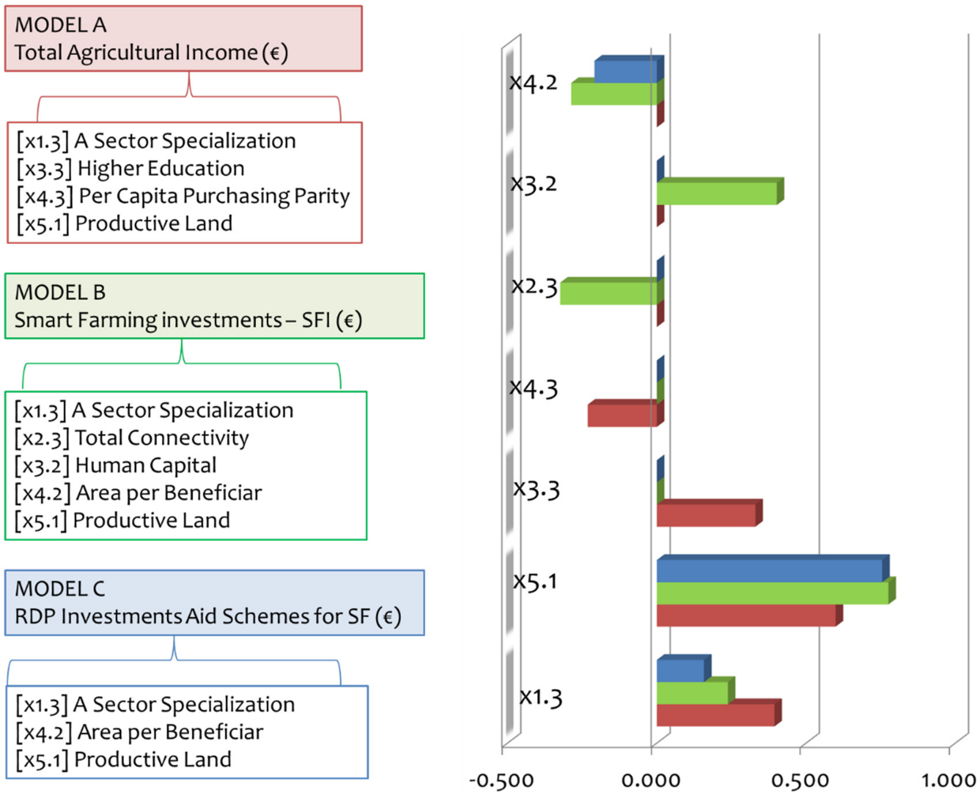



**Figure 7.** (**right**) Brace Map of the standardized BEM linear regression coefficients (designed with Lusidchart and (**left**) the corresponding Clustered Bar Charts (bar colors correspond to the model color) (Lusid Software Inc., Salt Lake City, UT, USA, https://lucid.app/lucidchart/, accessed on 20 February 2023) with only significant predictor variables.

### 3.2.1. Model A—Total Agricultural Income—TAI

In the first part of Table 2, model A (total agricultural income (TAI)) describes the standard income produced by all plants and animal production of beneficiaries (per NUTS 3 regional unit) that is declared in the Unitary Application for Aid Schemes (UASS) for the year 2018. Although the determination of this model is not high (adj.$R^2$ = 0.496), is acceptable to the extent that (i) it (asymptotically) describes the 50% of the variability of the response variable $\boldsymbol{y}_{\mathrm{A}}$ and (ii) results in four significant predictors, thus providing sufficient structural information according to our thematic grouping. According to this model, there are two significant predictors ("Productive Land (0.1 ha)", and "A Sector Specialization (%GDP)") at the 1% level and two significant predictors (Higher Education, Per Capita Purchasing Parity) at the 10% level of significance. The first predictor, "A Sector Specialization (%GDP)", belongs to productivity and agglomeration variables and has a positive contribution to the model. The positive model coefficient signifies that regions with a high specialization in the primary sector are more likely to have a high total agricultural income. This result describes the relative share that agriculture has in a country's GDP and highlights the importance of sectorial specialization to regional productivity and growth [57], which in terms of sustainability indicates reducing the assortment of diversity [58]. Further, the positive contribution of the "Productive Land" predictor in the model reveals the importance of the "land" productivity factor for sustainable land uses, nutrient availability, and crop yield response, as well as for economic efficiency [59]. In the context of the underlying (for this predictor variable) resource base theory, the significant participation of this predictor highlights the importance of the uneven distribution of natural resources ("Productive Land") for the increase in agricultural income, suggesting the nonstop existence of inequalities and reflecting unequal development in the rural economy [27]. Next, in model A, Higher Education (per capita) is positively related to agricultural income. This result describes thoroughly how knowledge-based economies affect the capitalization of innovation, indicating that, agricultural holdings investing in SFTs are located in regions with the rapid development of knowledge-based and innovation-based economies, rather than manufacturing-based neoclassical economies [60]. In other words, nowadays, digital transition has become one of the most notable features of capitalism and urbanization, leading to cognitive–cultural economies that foster creativity and innovative talent [61]. In the context of the underlying endogenous growth theory, this positive coefficient implies that knowledge intensity is an engine of agricultural growth. Finally, the fourth significant variable "Per Capita Purchasing Parity (EUR/citizen)" has a negative contribution to TAI. This negative result indicates that regions with high levels of purchasing parity are less likely to enjoy a high agricultural income, expressing a competitive relationship between the primary sector and regional welfare in Greece. Although the European Commission grants 25% of its total budget to be spent on structural funds to reduce economic disparities [62], this result for Greece addresses regional and agricultural policy directions towards sustainable rural development. In the context of the underlying economies of scale theory, this negative result can imply that economies of scale, which lead to higher levels of consumption and purchasing parity, do not suggest a growth engine of agricultural productivity, thus highlighting the effectiveness of the cumulative effect compared to the scale effect. In terms of regional policy, this interpretation allows conceiving policies of agricultural development based on the support of small and medium enterprises (SMEs), which drive regional economies to cumulative results, instead of economies of scale.

#### 3.2.2. Model B—Smart Farming Investments—SFIs

In the second part of Table 2, model B shows the results of smart farming investments (SAI) expressing the total cost of purchased equipment per NUTS 3 unit of the investments made. The determination of this model is high (adj.$R^2$ = 0.728), describing that over 72% of the response variable's $\boldsymbol{y}_{\mathrm{B}}$ variability is explained by five significant predictors. According to model B, two out of three positive affecting coefficients are "A Sector Specialization (%GDP)" and "Productive Land (0.1 ha)", which are common predictors with the first model, indicating that productivity and resources tend to influence SFTs purchased. Further, the positive contribution of "Human Capital" to the model indicates that labor quality is important to promote smart farming, to the extent that regions with a high human capital are more likely to enjoy higher SFIs. Human capital refers to the knowledge, skill sets, and experience that workers have in an economy; thus, human capital and economic growth have a strong relation. Human capital affects economic growth and can contribute to economic development by expanding the knowledge and skills of its people [63]. On the other hand, the remaining variables ("Area per Beneficiary (1 ha)" and "Total Connectivity (network degree)") are predictors contributing negatively to model B. In particular Regions with a high "Area per Beneficiary (1 ha)" are less likely to enjoy high SFIs. These results may relate to the fact that there are 684.950 small-size and family-run holdings in Greece, with most of the managers being over 55 years old and less than 10% of the managers being below 40 years old, a suspending fact for major transformations (such as the adoption of SFTs) in the farming processes [64]. Further, population aging affects adoption and eventually the evolution of the industry life cycle, delaying development and growth according to economies of scale theory [65]. In the context of the underlying economies of scale theory, this negative result illustrates that SFIs in Greece do not build on economies of scale (large areas) but on small investments promising cumulative instead of scale effects. This observation illustrates the early stage of SF in Greece, placed in the "chasm" area shown in Figure 1, where (according to model B) SFIs are running through an early adoption period incorporating low risk. Further, this observation proposes a good practice in regional policy building on the massive support of SMEs instead of large-scale enterprises. Finally, the negative contribution of the "Total Connectivity (network degree)" predictor in model B indicates those regions equipped with high transportation connectivity are less likely to enjoy high levels of SFI. This observation illustrates a competitive relationship between accessibility and SF, describing that SFIs currently apply to regional markets of small transport integration and consequent immature economic functionality. In the context of the underlying NEG theory, this outcome indicates that SF growth is currently more likely to follow centrifugal than centripetal forces and therefore to lead to the emergence of peripheral instead of central markets. A further interpretation may be linked to aging [66]; since NEG emphasizes what is called forward linkage as the driving force of agglomeration, the generational difference in a location incentive greatly influences network connectivity, and the lapse of it is causing large trade costs and ceteris paribus low-scale economies [67].

#### 3.2.3. Model C—RDP Investment Aid Schemes for Smart Agricultural Investments—AS-SAIs

In the third part of Table 2, model C describes the sum of the number of aid schemes that were financed through the RDP. The determination of this model is also high (adj. $R^2$ = 0.711), describing that over 70% of the response variable's $y_C$ variability is explained by three significant predictors. According to this model, predictors "Productive Land (0.1 ha)" and "A Sector Specialization (%GDP)" positively contribute to the variability of the response variable, whereas predictor "Area per Beneficiary (1 ha)" contributes negatively. On the one hand, the positive contribution of "A Sector Specialization (%GDP)" indicates that regions with a high specialization in the primary sector are more likely to enjoy high RDP investment aid schemes for SF. In the context of the underlying theories, specialization is a major stimulus of regional development building on the exploitation of the comparative advantage that intensity in production coefficients (labor, capital) offers to a region. Based on this interpretation, this result describes a "low-risk" model of regional policy, illustrating the state's expectancy over specialized regions in agriculture to better perform in SF and become more effective in SFIs. Further, the positive contribution of the "Productive Land" predictor in the model is in line with the previous commentary, illustrating the cognition of governance over the importance of the uneven distribution of natural resources towards the development of SF in Greece. On the other hand, the predictor "Area per Beneficiary (1 ha)" has a negative contribution to the model, illustrating that, petitioners in order to be selected as beneficiaries, were rated and ranked by the type of cultivations, the unit labor costs indicator, and the positive assertion of an evaluator.

The factors that were completely excluded from the model are those referring to the NEG and endogenous development theories. Since the goal of the program is to close the gap between regions to reduce economic disparities, those factors should be assessed by the evaluators to reinforce innovation investments. Moreover, since rural areas are more amenable to climate change impacts and climatic fluctuations and less economically resilient, the focus should be to encourage farmers to pursue innovative and eco-friendly types of investments to modulate negative effects on sustainable development [68,69]. The three dependent variables, total agricultural income (TAI) of holdings, smart farming investments (SAIs), and aid schemes for SAI (AS-SAIs), after the use of BEM that formed the models, are all positively significantly dependent on the factors "A Sector Specialization (%GDP)" and "Productive Land (0.1 ha)". In addition, among smart farming investments (SAIs) and aid schemes for SAI (AS-SAIs), there is a concurrency of the vector "Area per Beneficiary (1 ha)".

#### 3.2.4. Model Comparisons

To facilitate comparisons among the three available models, we constructed the bar charts shown in Figure 3, which illustrate the standardized model coefficients clustered by predictor variable, only for those cases exhibiting significant results. As can be observed, common variables in all three regression models are "A Sector Specialization (%GDP)" and "Productive Land (0.1 ha)". As far as the "A Sector Specialization (%GDP)" is concerned, we can observe a "declining" pattern across these three models, indicating that this predictor is more important for model A, less for model B, and even less for model C. In the context of the underlying theories, this outcome describes that sectorial specialization appears to be a more important growth engine for traditional rural agricultural development than for smart agricultural development, illustrating that the engine of the underlying agglomeration and comparative forces is more traditionally than "smartly" applicable in Greece. On the other hand, we can observe an opposite pattern describing the "Productive Land (0.1 ha)" predictor variable. In particular, the inequality $b_{X.5.1}$(A) < $b_{X.5.1}$(C) ≈< $b_{X.5.1}$(B) illustrates that productive land is more important for smart than traditional farming. In the context of the underlying theories, this inequality describes that resource allocation is a more important growth engine for smart than traditional agricultural development. To the extent that the resource base theory suggests an early generation theory of regional development [27], this outcome is also representative of the early stage of the SF's evolution in Greece, where the setting of growth foundations is required according to the tech innovation curve shown in Figure 1.

In terms of endogenous dynamics, we can observe in Figure 7 that predictors "Higher Education (per capita)" and "Human Capital" are significant for models A and B, respectively. In the context of their underlying theories, this observation implies that the knowledge-based transformation can provide an engine for both traditional and smart rural development by stimulating increasing returns of scale to the production mechanism [20,21,27]. In this observation, we can interpret the inequality $b_{X.3.3}$(A) < $b_{X.3.2}$(B) as relating higher knowledge-intensive dynamics to the SF model (B) than the traditional one (A). This implies the higher knowledge-based transformation that SF requires to drive sustainable development. Moreover, the definitive difference between these two variables (according to which human capital is better coordinated with production), reveals the "preferential" importance of SF development for production (labor) rather than total population dynamics (also including consumption). This conceptual difference highlights the "preference" or necessity of SFIs to enjoy medium rather than long-term returns of scale and thus a faster payoff than traditional agriculture, which runs the mainstream market according to Figure 1. This qualitative difference can provide a further indication of the conceptual effectiveness of the methodological approach applied in this paper.

To further discuss the structural dynamics of the three models, we constructed the cluster bar chart shown in Figure 8. This figure was generated from Figure 7 by grouping the independent variables according to their underlying theories. Provided that each theory is expressed by its representative variables, we can interpret that "traditional agriculture" (as represented by model A) is driven by dynamics described by the resource base, comparative advantage, and endogenous development theories, whereas it is restricted in terms of economies of scale. To the extent that (i) the resource base theory ensures sufficient inputs in the production coefficients, (ii) comparative advantage indicates viability against regional competitiveness, (iii) endogenous development theory promises development high increasing returns of scale, and (iv) economies of scale describe production engines benefited in input costs, the developmental profile of "traditional" agriculture appears to be (i) low-risk (high contribution of resource base variables), (ii) building on regional competitiveness and endogenous growth, and (iii) addressing further goals for regional policies towards supporting economies of scale (e.g., attracting large scale investments, developing smart farming parks).

Next, we can interpret that "smart" farming (as represented by model B) is driven by dynamics described by the resource base, comparative advantage, and endogenous development theories, whereas it is restricted in terms of new economic geography and economies of scale. In addition to the previous assumptions, to the extent that the new economic geography theory foresees development in regional (instead of central) markets in cases of restricted connectivity, the developmental profile of "smart" farming (i) appears even less risky than traditional agriculture, (ii) bets more on the endogenous growth dynamics, and (iii) addresses further goals for regional policies towards supporting economies of scale and improving accessibility for central markets' development. Finally, this analysis allows indicating that the support of the state for "smart" farming (as represented by model C) is driven by dynamics described by the resource base, comparative advantage, and economies of scale theories, shaping a low risk profile building on regional competitiveness and cumulative support of investments motivating SMEs [70,71].

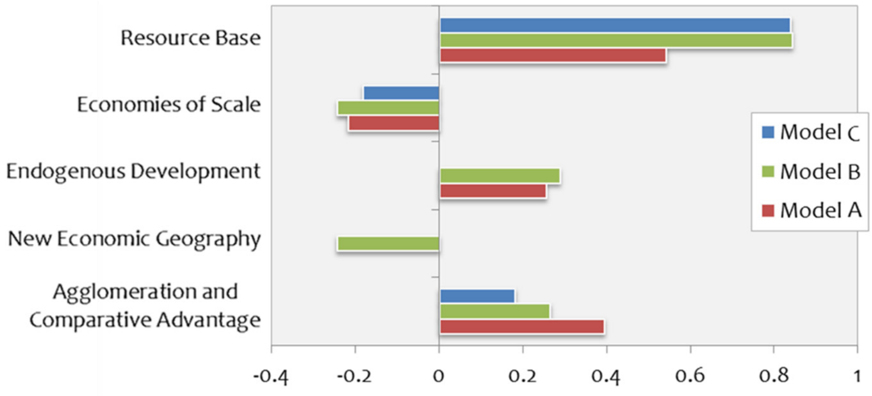



**Figure 8.** Clustered bar charts of the standardized BEM linear regression coefficients.

## 4. Conclusions

A great number of SFTs', were funded by the Rural Development Program of the European Union's "European Agricultural Fund for Rural Development" from 2018 to 2022 in Greece. With the data provided by the Greek Unit of Investments in Agricultural Holdings, we studied the agricultural income of holdings and their investments in smart farming to correlate them with factors affecting regional development based on six of the economic theories most common in the literature. We located patterns of geographical distribution and clarified the acceptance of usefulness in holdings in Greece. Moreover, aid schemes were assessed likewise to estimate the accessibility of smart farming technologies (SFTs) for holdings and gain insights into the implementation of policies, since according to Roger's diffusion of innovation social science theory, there are five established adopter categories, the innovators and the early adopters that translate conceptually to new products or ideas and the early/late majority and laggards that adopt after perceiving the usefulness of the early adopters and are unlikely to invest before they do. The chasm between them is a matter of consideration for the diffusion of innovation.

Hot spot spatial pattern analysis applied to the data, while not inherently predictive, also has the potential to assist in the rapid, consistent identification of priority areas for management intervention. The econometric analysis, which was built on a multilevel methodological framework, provided insights into quantifying digital transformation in agriculture. By selecting a set of predictor variables as representatives of major theories of regional and economic development, we constructed a multiplex multivariate regression model expressing "traditional" agriculture and SF, along with the state's subsidizing policy at the NUTS III administrative level. Several factors and indicators appeared to be significant, and to test the hypothesis, we selected indexes of performance, effectiveness, or efficiency of the factors affecting socioeconomic conditions according to each of the six described theories, and a triplet of multiple comparisons employing pairwise regression was applied. The first model estimated that agricultural income is affected by agglomeration and productivity, education, economies of scale, and resource-based theories. The second model showed that smart farming investments farmers made are related, in addition to all the above, to accessibility. The third model, strongly connected with the policies involved, is correlated with resources, economies of scale, and agglomeration and productivity theories. On the one hand, the analysis revealed some common features across the models, since are all described by (i) a low-risk income and investment strategy, which in the context of the resource base theory is conceived as plentitude in resource availability; (ii) a competitive strategy, which in the context of the competitive advantage theory is conceived by the comparative advantage of regions for specialization in agriculture; and (iii) preference for a production model of counter-economies of scale, supporting cumulative development based on SMEs. That is, both "traditional" and SF in Greece appear to build in common on resource availability and primary sector specialization, which indicates a "conservative" model of SF diffusion in Greece compared to the "modern" aspect that a digital transformation promises. On the other hand, the analysis showed that (i) sectorial specialization provided a more important growth engine for traditional than smart agricultural development; (ii) SF is more knowledge-intensive than traditional agriculture; (iii) resource allocation appeared a more important growth engine for smart than traditional agricultural development; (iv) SF investments (SFIs) correspond to medium rather than long-term returns of scale, seeking a faster payoff than traditional agriculture does; and (v) connectivity applies significant frictions to SFIs, setting the conditions for peripheral sprawl and the development of peripheral markets. Within this context, the analysis showed that SF currently runs through the early market stage and may stimulate its development through economies of scale and accessibility improvements. Overall, this paper developed a thematic quantitative approach for the evaluation of early changes of technological diffusion (where well-established methods such as input–output analysis is not applicable) and provided insights into the effect that SFTs have on sustainable regional development.

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