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Somewhere in between towns, markets, and neighbors: Agricultural transition in the rural-urban interface of Bangalore, India

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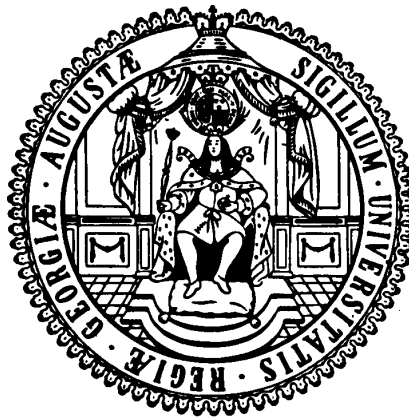
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**Somewhere in between towns, markets, and neighbors –
Agricultural transition in the rural-urban interface of
Bangalore, India**

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Somewhere in between towns, markets, and neighbors – Agricultural transition in the rural-urban interface of Bangalore, India

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Abstract

This paper presents a flexible conceptual and methodological framework to model the dynamics of agricultural transition in the increasingly complex rural-urban interfaces of large cities. Our empirical analysis is based on data of a household survey conducted in the rural-urban interface of Bangalore, India. In our analysis we follow a polycentric perspective of urbanization and introduce a two-dimensional variable to measure its effects. Furthermore, we accommodate high input and crop diversity by applying a Structured Additive Regression (STAR) model. Our results show that satellite towns and road infrastructure are the main channels by which urbanization drives agricultural transition. Access to satellite towns appears to be more strongly associated with the modernization of smallholders' management systems than access to the urban center of Bangalore. Our results suggest that more flexible models are necessary to understand the dynamics of agricultural transition in the surroundings of fast-growing large towns, the kind of town expected to be dominating the urbanization trend in the coming decades.

Keywords: Agricultural change, Urbanization, Structured Additive Regression, Geosplines, India

JEL: Q12, R11, C14

1. Introduction

Today more than half of the world population lives in cities and the trend points towards two-thirds in 2050 (United Nation Population Division, 2014). If urbanization has rather been a phenomenon of the developed world in the past, countries in Asia and Africa will dominate urbanization rates in the coming decades. Thus, it is not surprising that the relevance of urban centers in developing countries has been recognized in the field of development and agriculture economics. Recent studies regularly include proxies of urbanization to analyze the effects of cities on the livelihood or farm productivity of smallholders (e.g. Vandercasteelen, Beyene, Minten, & Swinnen, 2018b; Asfaw, Di Battista, & Lipper, 2016). The general idea is that proximity to an urban center improves access to markets, information, and technology and allows smallholders to modernize their production systems and improve their living standards (Chamberlin & Jayne, 2013). Common urbanization proxies are distance to the next city center or market, transportation costs, or travel times (Damania, Berg, Russ, Federico Barra, Nash, & Ali, 2016; Minten, Koru, & Stifel, 2013). The list is long and often variables are chosen based on characteristics of a region (e.g. topography, traffic conditions) or simple availability (Chamberlin & Jayne, 2013). Despite

these differences, the majority of studies show that proximity to urban centers and market access can significantly improve smallholders' livelihood and productivity.

Another development predicted by the United Nation Population Division (2014) is the trend towards larger cities and rapid expansion of existing medium-size cities (one to five million inhabitants) turning in to large cities (five to ten million inhabitants) or megacities (more than 10 million inhabitants). Hence, also the type of city and the rate of urban expansion might influence agricultural systems in the urban sphere. So far these aspects are hardly touched in the literature (exceptions are Vandercasteelen, Beyene, Minten, & Swinnen (2018a) and Christiaensen, Weerdt, & Todo (2013), who differentiate between different types of towns) but they might be crucial to understand rural-urban dynamics in the future.

In our study, we analyze determinates of agricultural transition in the rural-urban interface of Bangalore, a rapidly growing megacity in South Karnataka, India. In recent decades, Bangalore has exhibited exactly the behavior that will characterize future urbanization in many other parts of the world. Hence, our results are relevant for the future discussion of urbanization effects on agricultural production systems.

To carry out our analysis we had to confront three methodological challenges and we hope that our solutions will be useful for other studies facing diverse and complex rural-urban systems. In our sample of 640 farm households, we observed 72 different crops grown (first challenge) and more than 90 different inputs used (second challenge). A common approach when investigating determinants of agricultural modernization or intensification is to model the dichotomous decision of a farmer to adopt one modern input or not (e.g. new variety seeds or inorganic fertilizers) and often researchers do so by focusing on one crop or comparing separate estimations for different crops (Becerril & Abdulai, 2010). In the case of Bangalore, this procedure seems to be of limited use. The high crop diversity does not allow focusing only on a particular crop. If we aggregate inputs into broader categories such as inorganic fertilizer, we lose a lot of information and we might not be able to differentiate between nuances in the agricultural management behavior of smallholders. The third challenge is that Bangalore is surrounded by smaller satellite towns, which also provide farmers with market facilities and services. We therefore need to consider a polycentric urbanization model to explain agricultural transition in the rural-urban interface of Bangalore.

We approached these three challenges, first, by developing a conceptual framework that structures different pathways of urbanization effects on agricultural transition and, second, by applying a flexible Structured Additive Regression (STAR) model in the empirical analysis, which allows for multiple random effects and two-dimensional spatial effects.

The remainder of this paper is structured as follows. We set up the conceptual framework in section two. Then we present our data set and estimation method in section three. In section four we discuss our results and in section five we summarize our findings.

2. Conceptual Framework

To understand the interaction of urbanization and agricultural management, we focus on the farmer as decision-making unit (see Figure 1). Neglecting the diversity in crops and assuming we can perfectly measure agricultural management, we define three potential pathways through which farmers' management decisions can be influenced. Two of them are related to urban activities and one is independent of urbanization. Urbanization can affect the farmer either directly (Figure 1, 1) or indirectly

(Figure 1, 2). Direct effects include improved access to markets, knowledge, and technologies. Indirect effects result from, for example, off-farm labor opportunities or better education facilities. These do not directly influence the agricultural management of the farmer but the overall situation of the household and thus possibly also its agricultural decision-making. The independent effect (Figure 1, 3) refers to general socioeconomic characteristics such as age or caste, and plot characteristics.

In order to make this framework applicable for empirical analysis, we have to specify good indicators to measure the urbanization effects and agricultural transition.

Recent studies evaluating the effect of urbanization on agricultural systems often use distance to a city center or market to describe the influence of an urban center on a household. Distance does not necessarily mean physical distance; it rather represents a household's access to urban infrastructure such as markets, services, or knowledge (Damania, Berg, Russ, Federico Barra, Nash, & Ali, 2016). However, the measurement of the effect generally follows a one-dimensional, continuously increasing variable (e.g. travel time or transportation cost). The implication of such a proxy is that it has one exclusive point of reference, the center of a town or a market. Even studies considering a set of towns (Vandercasteelen, Beyene, Minten, & Swinnen, 2018a) generally assign a town of reference to every household. Thus, a household would not sell its produce in both city A and city B. However, this is exactly what we observe in the rural-urban interface of Bangalore. There are several smaller towns in direct proximity to Bangalore (50 km) with own market infrastructures. It is very likely that these towns are relevant for the decision-making of smallholders. If households are located between Bangalore and these secondary towns, it is not possible to identify one single town of reference.

As a consequence, a one-dimensional proxy might not be suitable to represent urbanization effects in our case. We have to assume that urbanization in the rural-urban interface of Bangalore is polycentric, i.e. urbanization effects result from more than one point in a plane. It might be that Bangalore is the central point and is indirectly responsible for the increasing importance of the smaller towns. Many products that farmers bring to a wholesale market in a satellite town might eventually end up in Bangalore. However, we are interested in the perspective of the smallholder and she will recognize Bangalore and the satellite town as two distinct market places. Following this assumption, we need a two-dimensional variable to measure the location effect of urbanization. That is the location of a household in the two-dimensional space is the aggregated effects of distances to potentially more than one town of reference. As in the one-dimensional approach location refers then to market access.

The word "transition" refers to a change from one state to another. Hence, in the agricultural context, we mean the transition from one form of agriculture to another. In this study, we are interested in the transition from a traditional management system to a more modern and sophisticated one. In accordance with most of the literature (e.g. Christiaensen, Weerdt, & Todo, 2013; Chamberlin & Jayne, 2013), we assume that smallholders applying modern production techniques and technologies are more likely to escape poverty and improve their living standards. Therefore, we want to analyze the ways urbanization might accelerate the transition to more modern agricultural management systems.

As agricultural transition refers to the overall agricultural management strategy of a household, we have to find a variable that is appropriate to represent this aspect. A large part of the literature investigating agricultural management practices focuses on single inputs or technologies. The technologies under observation depend on the focus of the studies. Some are interested in the adoption of new seed varieties (Smale & Olwande, 2014; Becerril & Abdulai, 2010), others analyze the adoption of inorganic and

mineral fertilizers (Lambrecht, Vanlauwe, Merckx, & Maertens, 2014). Studies more interested in the intensity of inputs use consider quantities of different inputs (Vandecasteele, Beyene, Minten, & Swinnen, 2018a). However, all these studies conduct a separate estimation for every technology. If one wants to use this approach to analyze the transition of agricultural management systems, one must identify one technology that characterizes the whole system. Such a choice is very difficult, especially in a setting like the rural-urban interface of Bangalore, where the farm households are very heterogeneous. For example, in our data set we recorded 27 different inorganic fertilizers, 11 different insecticides, and 10 different fungicides being used by smallholders. As a consequence, quantities cannot be used as some of the fertilizers or pesticides are not comparable and aggregating inputs in broader classes to construct a dichotomous adoption variable might lead to a loss of information.

We therefore aim to construct a variable that relies on a basket of technologies representing the state of agricultural transition of every household. Some studies pursue a similar approach, however with a different research focus. Teklewold, Kassie, & Shiferaw (2013) analyze the adoption of sustainable agricultural practices in Ethiopia allowing for different combinations of practices. Wollni, Lee, & Thies, (2010) are interested in the adoption of conservation agriculture. For this purpose, they define conservation agriculture as a package of different practices of which a farmer might only adopt some. Sharma, Bailey, & Fraser (2011) call this a “multiple technology selection problem” (p.75) in their study on pest control strategies in the UK. They respond to the problem by using the sum of all adopted practices as dependent variable (Wollni, Lee, & Thies, 2010; Sharma, Bailey, & Fraser, 2011; Lohr & Park, 2002). They interpret the sum as intensity of adoption or complexity of adoption portfolio. This interpretation is valid because they focus their count only on practices relevant to their research question, i.e. pest control strategies (Sharma, Bailey, & Fraser, 2011) or insect management techniques (Lohr & Park, 2002). Hence, the more practices are adopted the more involved is the farmer in this particular aspect of agricultural management.

This approach seems more suitable for our study, if we can identify a class of technologies or practices characterizing a modernized agricultural management system. We propose that modern seasonal inputs are a good fit for this purpose. They include any type of new seed variety, pesticides, and inorganic fertilizers. Certainly machinery and irrigation technologies could also be a good indicator for the transition state of a smallholder’s management system. However, these are long-term investments. That means also the timing of the adoption is important to understand the transition of the management system. Because we only have cross-sectional data, we are not able to determine these dynamics. Instead, we assume that every season the smallholder makes a new decision about the seeds, pesticides, and fertilizers he wants to buy, and we model the transition state of his smallholding as the number of all adopted modern inputs.

After specifying our understanding of urbanization and agricultural transition, we are able to formalize the decision-making of the smallholder. For this we adopt the model of Vandecasteele, Beyene, Minten, & Swinnen (2018a, 2018b) who model input demand considering the effect of distance to an urban center. We replace the distance variable by our location effect. Further we assume that the sum of all modern inputs is the result of dichotomous decisions over all available modern inputs. Following the logic of Sharma, Bailey, & Fraser (2011) the choice of one modern input does not automatically exclude other modern inputs from the farmer’s management portfolio.

Hence, we describe the farmer's decision-making as a profit maximization problem, which allows for effects of the household's location l and simultaneous choice of modern inputs x_i , $i = 1, \dots, k$. A farmer produces an output Y using a set of modern inputs X . His production function can be written as:

$$Y = A(l)f(x_1, \dots, x_k) = Y(l, x_1, \dots, x_k) \quad (1)$$

where $A(l)$ is a productivity shifter representing direct effects of the household's location (l) on agricultural productivity. In the distance setup of Vandercasteelen, Beyene, Minten, & Swinnen (2018a, 2018b) this effect refers. For example, to better information and extension services in proximity to an urban center.

In addition, the price a smallholder receives for his produce and the price he has to pay for an input x_i depends on the location of the household. There will be a certain amount of cost incurred to reach the markets, i.e. transportation costs $\mu(l)$. Thus, we describe effective output (2) and input prices (3) as functions of the household location.

$$p = p^M - \mu(l) = p(l) \quad (2)$$

$$w_i = w_i^M + \mu(l) = w(l) \quad (3)$$

For households not selling their produce in a market, the effective output price $p(l)$ represents the value the produce has as consumption or fodder good. Purchasing consumption or fodder crops also leads to a space-defined additional cost. Consequently, the value of a produced crop for home consumption or further agricultural use has a space-dependent value.

After defining (1) to (3), we have all elements to write down the profit function to be maximized by the smallholder (4). We understand it as the farmers search for the optimal set of modern inputs x_1, \dots, x_k depending on his location (l) in the geographic plane.

$$\pi(x_1, \dots, x_k) = \max(p(l)Y(l, x_1, \dots, x_k) - \sum_{i=1}^k w_i(l)x_i) \quad (4)$$

The idea is that the farmer assigns an expected profit to every possible set of modern inputs x_1, \dots, x_k . He is doing so by taking a certain set of inputs and then deciding whether to add another input x_i . The selection criterion for input x_i can be described as (5).

$$E[\pi(x_i | x_1, \dots, x_k)^{s_{x_i=1}}] - E[\pi(x_i | x_1, \dots, x_k)^{s_{x_i=0}}] > 0 \quad (5)$$

A farmer includes the additional input x_i in his current portfolio x_1, \dots, x_k if he expects the profit of the addition ($s_{x_i=1}$) to exceed the profit of the input portfolio without the addition ($s_{x_i=0}$).

Vandercasteelen, Beyene, Minten, & Swinnen (2018b) considered a two-input model in their study and derive the optimal demand of both of these inputs by solving the first order criterion. As we are only interested in the decision whether an input is added to a portfolio or not, the exact demand of an input is secondary to our research interest. However, the exercise of Vandercasteelen, Beyene, Minten, & Swinnen (2018b) clearly identifies the pathways how distance to an urban center affects the optimization of input demand. The derivation for the two-input case is already quite complex; a system of k inputs would require the numerical solution of a k -equation system. This would be beyond the scope of this paper.

Nevertheless, we can assume that the pathways identified by Vandercasteelen, Beyene, Minten, & Swinnen (2018b) are also valid for a model with more than two inputs. Further, if they are relevant to determine the optimal demand of the different inputs, they will also be relevant for the decision to take up an input into the portfolio in the first place. Accordingly, there are four types of effects that contribute to the overall location effect elaborated before: a) an own price effect of the input, b) an effect of the output price, c) an direct productivity effect, and d) an cross-price effect of all other input prices included in the set x_1, \dots, x_k .

If we use the aggregated interpretation of the location effect as market access, following Vandercasteelen, Beyene, Minten, & Swinnen (2018b) the better the market access the higher should be the agricultural transition of the household. However, because neither market access nor location are necessarily a linear functions of geographic distance, we cannot yet hypothesis where we will find higher degrees of agricultural transition in rural-urban interface of Bangalore.

Nevertheless, this framework will be of good use in the discussion of our empirical analysis, in which we use a statistical model that directly estimates location effects and analyze how it influences the number of adopted modern inputs. Furthermore, we are interested in the general mechanisms of agricultural transition in the rural-urban interface of Bangalore.

3. Data and methods

3.1 Data

For our empirical analysis we use data from a socioeconomic survey conducted in early 2017 in two transects cutting through the rural urban interface of Bangalore in South Karnataka. The survey covers about 1200 households, which were randomly selected in a two-step procedure. First, villages were randomly selected out of the total number of villages in both transects.¹ In a second step, households were randomly drawn from household lists provided by the preschool teachers of every village.

In our study we focus on agricultural management. Therefore, we only considered households involved in agriculture. As a consequence, our sample contains 640 farm households; 354 households in the northern and 286 households in the southern transect. Figure 2 shows the villages in which these agricultural households are located. Next to the coordinates of the village centers, we also collected GPS coordinates for all households.

To fully represent the transition of agricultural systems, we collected in-depth information about the agricultural management and marketing practices of the year 2016. In that way, we obtained a complex data set with information on different scales. The smallest scale is the crop level with data on irrigation or input use, for example. Additional scales are plot, household, village and transect. At the crop level we worked with 884 crop observations in the northern and 1037 observations in the southern transect.

As outlined in the previous section, we represent the state of agricultural transition as the sum of modern inputs used by a farmer. We asked every farmer for a complete list of inputs he used for every crop he grew in 2016. Afterwards we classified all inputs into the categories of (a) organic fertilizer, (b) traditional seed varieties, (c) new seed varieties, (d) pesticides, (e) inorganic fertilizer, and (f) hormones. For the count of modern inputs we considered all inputs classified in categories c to f.

¹ For detailed information on the village selection see Hoffmann, Jose, Nölke, & Möckel (2017).

To measure the location effects we propose using two-dimensional splines. We compare the results of this approach with three alternative measures, i) the distance to the city center of Bangalore, ii) the built-up area (village level), and iii) an index introduced by Hoffmann, Jose, Nölke, & Möckel (2017), the Survey Stratification Index (SSI). The SSI is calculated as the geometric mean of the normalized distance to the city center and the normalized non-built-up area (Hoffmann, Jose, Nölke, & Möckel, 2017).² These three proxies were very interesting for our study. The distance to the city center of Bangalore, represents the classical monocentric perspective of urbanization effects and we can investigate to what extent it fits the Bangalore case. The built-up area is independent of the Bangalore focus only considering structures in the direct proximity (1 km radius) of every village. In a way, it represents the other extreme to the monocentric perspective. The SSI is the compromise between both acknowledging the importance of the mega city and also including other village specific features.

3.2 Methods

We chose a Structured Additive Regression (STAR) model for estimation. Following Sharma, Bailey, & Fraser (2011) and Fahrmeir, Kneib, Land, & Marx (2013), we assume that the dependent variable (counted number of modern inputs used) is Poisson distributed. To ease interpretation we use the log-linear form of the Poisson model. The important difference between the standard linear Poisson model and the STAR Poisson model is that the latter allows for additional types of covariates next to the classical linear effects (Fahrmeir, Kneib, Land, & Marx, 2013), in our case accounting for data at multiple scales and two-dimensional spatial effects. Hence, we built a semiparametric predictor out of four different effects:

$$\log(\lambda_i) = \eta^{struc} = \mathbf{X}\boldsymbol{\beta} + \mathbf{f} + \boldsymbol{\gamma} + \mathbf{f}_{geo} + \boldsymbol{\varepsilon}, \quad (6)$$

$$\text{with } y_i \sim Po(\lambda_i)$$

$\mathbf{X}\boldsymbol{\beta}$ is a vector of normal linear effects, \mathbf{f} is a vector of non-linear effects of univariate continuous variables, $\boldsymbol{\gamma}$ is a vector of scale-specific random intercepts, and \mathbf{f}_{geo} is a vector a two-dimensional spatial effects. In table 1, we present all covariates included as linear or univariate non-linear effects.

Inference of model (6) is based on a mixed model representation and estimation follows an empirical Bayesian approach; from a frequentist perspective it is comparable to penalized likelihood estimation. The main difference between both perspectives (Bayesian and frequentist) is the definition of the penalty in the non-linear smoothers of \mathbf{f} and \mathbf{f}_{geo} , either as variance component or smoothing parameter (Kneib & Fahrmeir, 2006)³.

The non-linear effects of the continuous covariates v_1, \dots, v_q in $\mathbf{f} = (f(v_1), \dots, f(v_q))'$ are estimated as penalized splines (P-splines) smoothers with a second-order penalty and 20 knots. The effect is therefore non-parametric and we do not have to specify any functional form prior to the estimation.

² For more information on the construction of all three proxies of urbanization see Hoffmann, Jose, Nölke, & Möckel (2017).

³ The estimation of the model was conducted in R using the package “R2BayesX” (Umlauf, Adler, Kneib, Lang, & Zeileis, 2013), which provides an interface to the free Software “BayesX” for Bayesian inference (Brezger, Kneib, & Land, 2005). For more information on the estimation techniques and inference see Kneib & Fahrmeir (2006), Umlauf, Adler, Kneib, Lang, & Zeileis (2015), and Fahrmeir, Kneib, Land, & Marx (2013).

The random intercepts are introduced to deal with scaling of the data. Because the city center of Bangalore separates the two research transects, we assume that there is no connection between the households of the northern and the southern transect. Therefore, we estimate separate models for each transect. This leaves potential random effects on the crop, plot, household, and village level, $\mathbf{Y} = (Y_{crop}, Y_{plot}, Y_{household}, Y_{village})'$. The crop level is especially important due to the high crop diversity observed in our sample. We introduce random effects for the different crops which allow each crop to have an individual random intercept representing its individual input requirements. However, beside this intercept the decision behavior – and thus the parameters to be estimated – is the same over all crops.⁴

The spatial effect f_{geo} is estimated as a two-dimensional P-spline surface smoother (geospline). This smoother estimates the direct effect of household or village coordinates (bivariate variable), $\mathbf{f}_{geo} = (f(S_{household}), f(S_{village}))'$, on the number of adopted modern inputs. It can be interpreted as a bivariate non-linear effect that results purely from a position in the plane and thus capture complex location effects in a polycentric setting.

With four potential random effects and two spatial effects, the proposed model is large and might not always converge. We therefore use the Akaike information criterion (AIC) to decide which of these effects should be included in the estimation. We start the selection procedure with the estimation of (6) only including $\mathbf{X}\boldsymbol{\beta}$ and \mathbf{f} in the predictor (we refer to this first estimation as “base”). Afterwards we add the random effects starting with the smallest scale (crops). If the AIC improves, the effect remains in the estimation, if not, it is excluded. Finally, we added the household and village spatial effect following the same procedure. After determining the final specification of the model (hereafter referred to as “final model”), we separately add the three urbanization proxies SSI, built-up area, and distance to evaluate the extent to which they coincide with the purely statistical effect \mathbf{f}_{geo} .

4. Results and Discussion

Tables two and three summarize the linear effects of the base and final model with the lowest AIC in the first two columns. The following three columns show the estimation results after adding each of the three urbanization proxies. The last model specification (last column) only includes the urbanization proxy with the lowest AIC and no two-dimensional spatial effect \mathbf{f}_{geo} .

For both transects the lowest AIC in the final model (6) obtains when random intercepts for the crop and the village scale, and a geospline for the village center coordinates are included. This model outperforms models with household random effects and spatial effects of household coordinates. This means that the village effects are stronger than the individual household effects. One possible reason could be that smallholders are likely to interact and learn from neighbors or are at least influenced by the same factors (e.g. soil fertility, water availability) to determine their agricultural management practices.

Looking at the significance pattern in either table we see that estimation results are quite robust through all presented model specifications in each transect. However, between the two transects the variables with significant effects differ⁵. The only variable that had a positive significant effect on the number of adopted

⁴ The interpretation for the other random effects is equivalent.

⁵ The results of the non-linear effects are not presented here because they are insignificant in both transects. However, they are available on request.

modern inputs in both transect was irrigation. This is quite intuitive as the access to irrigation is often a prerequisite of modern and intensified agricultural systems (Elliott, et al., 2014). Next to that, in the northern transect the household size, the ownership of a car, and the intention to sell the agricultural produce in the market led to an increasing number of adopted modern inputs. Also seasonal planting compared with perennial crops had a positive effect on agricultural transition. In comparison, extension services supported agricultural transition in the southern transect, whereas this effect remains insignificant in the northern transect. In addition, the exclusive use of agricultural produce as fodder significantly decreased the number adopted modern inputs. The fodder purpose of agricultural produce might be understood as the counter position of the marketing purpose in the northern transect. Furthermore, even if the marketing effect stayed insignificant in the southern transect, the relatively small standard errors are still pointing towards some relevance.

Interestingly, also the number of off-farm jobs in a household significantly decreased the number of modern inputs. This suggests that off-farm employment slows down agricultural transition. This might seem counterintuitive as capital earned in the off-farm sector can be used in farm activities and thus contributes to agricultural transition (see e.g. Barrett, Bezuneh, & Aboud, 2001; De Janvry, Sadoulet, & Zhu, 2005). However, households also face a trade-off when deciding how to allocate labor resources between agriculture and non-agriculture (Huang, Wu, & Rozelle, 2009). If more advanced agricultural management practices require more especially skilled labor, which has high opportunity costs especially in a dynamic economic setting such as Bangalore, a household might rationally decide to remain in a lower state of agricultural transition. This dynamic in context of urbanization might be an interesting focus for a future studies.

Before we turn to the discussion of the spatial effect, we have to clarify some terminology so we do not mix up definitions of the conceptual framework and the STAR model. The location effect of the conceptual framework is an urbanization effect. It can be understood as the two-dimensional version of the commonly used proxies of market access such as distance or travel time. The spatial effect f_{geo} is however not automatically an urbanization effect. It represents the effect the physical location of a village has on agricultural transition. This effect can result from urbanization factors but it can equally refer to geological or biophysical characteristics of this position. Regardless of this problem, in section 3.2 we stated that this spatial effect is our attempt to model a two-dimensional urbanization effect, namely the location effect. We thought that the equation of the location and spatial effect is valid in our case for two reasons: First, we included plot characteristics such as soil quality and slope in our estimation. Thus, we ruled out small-scale biophysical factors. In addition, the random intercept of the village corrects for potentially unobserved factors. Second, the area of the research transects is rather small, so we do not expect larger geological or biophysical heterogeneity, which is not yet controlled by the variables described before. As consequence, we assumed that the spatial effect f_{geo} estimate in our empirical analysis equals the location effect elaborated in the conceptual framework.

Following the argumentation above the random effect of the village also contains a certain kind of spatial information. Random effects are generally applied to control for unobserved heterogeneity. Fahrmeir, Kneib, Land, & Marx (2013) however point out that they can also be interpreted as unstructured spatial effects, whereas effects estimated based on precise location information such as coordinates are structured spatial effects. In order to present the whole spatial heterogeneity in the estimation results, we present both the village structured spatial effect (location effect) and the village unstructured spatial effect (random effects) (Figures 4-6).

The location effect in the northern transect (Figure 3, a) shows a clear gradient from a negative effect on agricultural transition in the villages closer to Bangalore to a positive effect in the villages further away from the megacity. This result was unexpected. Recent literature generally shows that technology adoption increases with proximity to an urban center and market access (e.g. Vandercasteelen, Beyene, Minten, & Swinnen, 2018a). Following a monocentric perspective the location effect should be positive in the villages closest to Bangalore and decreasing in villages further away. However, in the northern transect the effect is reverse. One possible explanation might be the satellite towns of Doddaballapura and Chickballapura, which are located very close to the northern transect. These two towns also have market centers and might be better accessible to farmers due to lighter traffic than Bangalore itself. Also prices should be competitive to the ones in markets in Bangalore. For example, the APMC (state-run) wholesale markets in Doddaballapura and Chickballapura report that the majority of their commodities end up in markets in Bangalore⁶. This exchange should lead to a high degree of price integration. This suggests that the urbanization effect originates in the megacity Bangalore but is projected to less proximate households via integrated satellite markets. In that way we can explain the inverse gradient. It is less influenced by the pure distance to the center of the megacity but by its influence on surrounding smaller towns, which then are an attractive marketing alternative for smallholders.

After estimating the final model, we added the three urbanization proxies to the model (Table 2, columns 3-6) to see how their effects interact with the estimated location effect. The model specification with the SSI (column 3) results in the lowest AIC for the northern transect, and we see in Figure 4 that including the SSI almost completely eliminates the location effect. This phenomenon is referred to as confounding and results from multicollinearity between the spatial effect and a covariate (Hodges & Reich, 2010; Paciorek, 2010; Fahrmeir, Kneib, Land, & Marx, 2013). Generally, confounding is problematic as it can alter estimation results substantially (Hodges & Reich, 2010). However, in our case we used it to compare the location effect against the effect of the urbanization proxies. For the northern transect it seems that the two effects were quite equivalent. The missing location effect in Figure 4a implies that the effect of the SSI can explain almost the same spatial variation as the location effect. The AIC of both models also indicates that both effects are equally suitable to capture the urbanization effect. However, the interpretation of the effect of the SSI is slightly different. As it partially relies on the distance to Bangalore it is a monocentric measure. Thus, the positive effect of the SSI suggests that the more “rural” a village is the higher will be the degree of agricultural transition. This corresponds with the inverse gradient found in the location effect. Nevertheless, as the location effect does not classify villages along a rural-urban gradient, the options to explain the effect – for example, with satellite towns – are more straightforward.

In the southern transect the pattern of the location effect (Figure 5, a) is less clear than in the northern transect. It seems that the road connecting Bangalore and Kanakapura (Figure 2) plays some role. The further villages are away from the road the smaller (or negative) is the effect. That makes sense in the way that the road represents better access to the markets in Bangalore and Kanakapura. In the estimation with the three proxies, distance yields the lowest AIC. Figure 6 shows the location and unstructured spatial effects. Unlike in the case of the northern transect, the proxy shows hardly any confounding with the location effect but with the unstructured spatial effect (random effects). There are two possible explanations: (a) Assuming distance is a good indicator of urbanization, the structured spatial effect is not equal to the location effect. That would imply that there is non-urban spatial heterogeneity in the transect. As the negative location effect in Figure 5a coincides with a large lake in the east of the transect (Figure 2), there

⁶ <http://www.agmarknet.gov.in/MarketProfile/MarketProfile.aspx>, visited last time 12.01.2018.

might be non-urban structures exceeding the control of the village random effect. Or (b) distance being an urbanization proxy with a clear monocentric perspective does not appropriately represent urbanization effects in the southern transect. This would fit our interpretation of a positive location effect along the road connecting Bangalore and Kanakapura. This road facilitates not only the access to markets in Bangalore but also in Kanakapura. A monocentric perspective is therefore not appropriate. Support for the latter explanation comes from the AIC. The model including only the structured spatial effect (column 2) has a lower selection criterion than the model only including distance (column 6). Furthermore, even if distance was more appropriate to model urbanization than the location effect, not including the structured spatial effect would mean neglecting a significant spatial heterogeneity, which could lead to a bias in the estimation of other covariate effects.

Summarizing the analysis of the location effects, we find it to be a suitable way to model urbanization effects on agricultural transition in a polycentric urban scenario. In some cases the effect coincides with one-dimensional urbanization proxies; however, in other cases it gained better results. It appears that satellite towns and connecting roads in transmitting the urbanization effect originating in Bangalore.

Finally, we refer to the indirect effects described in the conceptual framework. If there are indirect urbanization effects, this means an interaction of covariates and the location effect, i.e. confounding. However, in both transects effects of covariates are robust and do not change location effects are added (Tables 2 and 3, column 2). Therefore, we do not observe indirect urbanization effects in the rural-urban interface of Bangalore.

5. Conclusion

In order to investigate agricultural transition in the rural urban interface of Bangalore, we first had to overcome three methodological challenges: 1) high input diversity, 2) high crop diversity, and 3) the presence of satellite towns requiring a polycentric perspective on urbanization effects.

We address input diversity by constructing the depending variable of our analysis as the number of adopted modern inputs. We interpret this variable as an indicator of agricultural transition. We control for the crop diversity by including random crop effects. To handle the polycentric urbanization effect, we introduced a two-dimensional variable to directly estimate the location effect. This effect allows for more than one reference town or point in space to define the market access of a household. In the empirical analysis, we estimated this effect as a structured spatial effect based on the coordinates of households or village centers.

Our results show that the structured spatial effect is a suitable approach to model urbanization effects in a polycentric setting. It performs at least as well as one-dimensional urbanization proxies such as the SSI or physical distance; in the southern transect it outperforms the own-dimensional proxy. Its interpretation is also more flexible because it is not tied to an own-dimensional gradient (e.g. rural-urban).

We identify two pathways through which urbanization effects increase agricultural transition. First, satellite towns seem to have a significantly positive effect on the adoption of additional modern inputs and seem to be better accessible, at least in terms of purchasing inputs and marketing outputs, for smallholders than the megacity Bangalore itself. Second, proximity to a main road facilitates agricultural transition as well. Also in this case, improved access to input- and output markets is a likely explanation.

Next to the spatial considerations, there are some distinct differences in the determinants of agricultural transition in both transects. Whereas seasonal effects and the intention to market the agricultural produce play an important role in the northern transect, off-farm employments and the production of fodder crops decrease the number of adopted modern inputs in the southern transect.

Thus, we show that there are several interacting pathways between urbanization and agricultural transition. Depending on the particular setting of the households one or the other pathway will dominate. Settings can already change in the rural-urban interface of a single city and we should expect to see even more variation in patterns and rates of transition if we expand the view to include other cities. This all suggests that there is a need for more flexible concepts and methods to model the effects of fast-growing large cities on the agricultural systems in their surroundings.

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Table 1. Definition of variables included for estimation.

	Variable	Description
Plot characteristics	Soil quality	1:Poor, 2:Middle, 3:Very good
	Slope	1:None, 2:Moderate, 3:Steep
	Plot property	1:Owned, 2:Rented, 3:Common area, 4:Government (permission), 5:Government (no permission)
	Irrigation	1:Yes, 0:No
	f(Time to plot)	Minutes to reach plot
	f(Size)	Size of plot (acres)
Agricultural characteristics	Dairy	1:Yes, 0:No
	Extension	1:Yes, 0:No
	Purpose production	1: Marketing, 2: exclusively fodder, 3: fodder and home consumption, 0: none of the others
	Sowing season	1: Kharif 2015, 2: Rabi 2015, 3: Summer 2016, 4: Kharif 2016, 5: Rabi 2016, 0: continuously
Socioeconomic characteristics	Caste	1:General, 2:SC, 3:ST, 4:OBC, 5: None, 7:Other
	f(Age)	Age household head
	f(Education)	Years of education (hh head)
	Household size	number hh members
	Number off-farm	Number of off-farm employments (household)
	f(Experience)	Years of farming experience (hh head)
	Car	1:Yes, 0:No
Urbanization proxies	SSI	Weighted index over built-up area and distance
	Built-up area	Built-up area in 1km radius around village
	Distance	km to city center of Bangalore

Continuous variables included as non-linear effects are marked as f(.).

Table 2. Linear effects, STAR model, northern transect (The second columns “Final” refers to the model specification including the spatial effect but no urbanization proxies; random effects included for crop and village scale.)

Variable	Factor	(1) Base	(2) Final	(3) SSI	(4) Built-up	(5) Distance	(6) SSI (no location effect)
Intercept		-0.1249 (0.3404)	-0.1260 (0.3384)	-0.6796* (0.3820)	0.0546 (0.3395)	-0.4925 (0.3672)	-0.6717* (0.3768)
Household size		0.0259** (0.0126)	0.0266** (0.0125)	0.0304** (0.0124)	0.0284** (0.0124)	0.0294** (0.0125)	0.0291** (0.0122)
Soil quality	2: Middle Reference: Poor	-0.0125 (0.1978)	-0.0266 (0.1977)	-0.0381 (0.1969)	-0.0189 (0.1973)	-0.0314 (0.1974)	-0.0477 (0.1966)
	3: Very good	-0.1093 (0.1996)	-0.1191 (0.1993)	-0.1237 (0.1986)	-0.1046 (0.1991)	-0.1181 (0.1990)	-0.1343 (0.1982)
Slope	2: Moderate Reference: None	-0.0121 (0.0705)	-0.0191 (0.0709)	-0.0232 (0.0690)	-0.0320 (0.0693)	-0.0197 (0.0700)	-0.0290 (0.0679)
	3: Steep	0.2002* (0.1195)	0.1946 (0.1196)	0.1763 (0.1184)	0.1560 (0.1186)	0.1855 (0.1191)	0.1710 (0.1177)
Car	Yes	0.2837** (0.1179)	0.3203*** (0.1176)	0.3539*** (0.1149)	0.2925** (0.1161)	0.3420*** (0.1176)	0.3760*** (0.1124)
Caste	2: SC Reference: General	-0.1348 (0.1211)	-0.1391 (0.1214)	-0.1798 (0.1175)	-0.1769 (0.1170)	-0.1625 (0.1198)	-0.1882 (0.1151)
	3: ST	-0.1996 (0.1423)	-0.1954 (0.1414)	-0.2127 (0.1347)	-0.2085 (0.1335)	-0.2009 (0.1393)	-0.2202* (0.1301)
	4: OBC	-0.0101 (0.0770)	-0.0086 (0.0766)	-0.0130 (0.0755)	-0.0139 (0.0761)	-0.0153 (0.0763)	-0.0156 (0.0747)
	7: Other	-0.2017 (0.1772)	-0.2138 (0.1770)	-0.2595 (0.1753)	-0.1937 (0.1736)	-0.2542 (0.1772)	-0.2639 (0.1738)
Plot property	2: Rented Reference: Owned	-0.1398 (0.1426)	-0.1310 (0.1423)	-0.1140 (0.1412)	-0.1286 (0.1408)	-0.1197 (0.1420)	-0.1102 (0.1405)
	3: Common area	0.0218 (0.7384)	-0.0374 (0.7371)	-0.0696 (0.7351)	0.0917 (0.7399)	-0.0643 (0.7371)	-0.0978 (0.7335)
	4: Gov. land (permission)	0.0301 (0.3339)	0.0333 (0.3334)	0.0186 (0.3317)	0.0450 (0.3307)	0.0243 (0.3329)	0.0154 (0.3307)
	5: Gov. land (no permission)	0.0598 (0.3342)	0.0615 (0.3340)	0.0765 (0.3329)	0.0636 (0.3332)	0.0756 (0.3334)	0.0724 (0.3324)
extension	Yes	0.0492 (0.0828)	0.0347 (0.0823)	0.0187 (0.0815)	0.0272 (0.0811)	0.0280 (0.0823)	0.0134 (0.0806)
dairy	Yes	-0.0187 (0.1784)	-0.0227 (0.1779)	-0.0275 (0.1763)	-0.0184 (0.1768)	-0.0258 (0.1771)	-0.0227 (0.1757)
Irrigation	Yes	0.2099** (0.1034)	0.2148** (0.1032)	0.2267** (0.1026)	0.2250** (0.1026)	0.2197** (0.1030)	0.2313** (0.1022)
Purpose	1: Marketing Reference: None of the others	0.2957*** (0.0978)	0.2954*** (0.0977)	0.3015*** (0.0974)	0.3088*** (0.0976)	0.3015*** (0.0977)	0.2970*** (0.0969)
	2: Exclusively fodder	-0.0918 (0.1355)	-0.0980 (0.1353)	-0.0991 (0.1351)	-0.0935 (0.1352)	-0.0964 (0.1353)	-0.1044 (0.1348)
	3: Fodder and Home consumption	0.1106 (0.0950)	0.1082 (0.0949)	0.1158 (0.0947)	0.1212 (0.0946)	0.1155 (0.0949)	0.1129 (0.0944)
Sowing season	1: Kharif 2015 Reference: Continuously	0.2440 (0.2773)	0.2476 (0.2767)	0.2689 (0.2753)	0.2395 (0.2756)	0.2677 (0.2765)	0.2593 (0.2742)
	2: Rabi 2015	0.3394** (0.1705)	0.3380** (0.1704)	0.3571** (0.1703)	0.3918** (0.1709)	0.3447** (0.1705)	0.3605** (0.1698)
	3: Summer 2016	0.3075* (0.1754)	0.3009* (0.1752)	0.2917* (0.1747)	0.3296* (0.1746)	0.2892* (0.1752)	0.2955* (0.1741)
	4: Kharif 2016	0.2989* (0.1575)	0.2974* (0.1572)	0.3071* (0.1570)	0.3295** (0.1566)	0.3008* (0.1574)	0.3080** (0.1564)
	5: Rabi 2016	0.5018*** (0.1817)	0.4983*** (0.1815)	0.4979*** (0.1810)	0.5309*** (0.1803)	0.4958*** (0.1816)	0.4991*** (0.1803)
number off-farm		0.0109 (0.0407)	0.0127 (0.0406)	0.0156 (0.0401)	0.0046 (0.0403)	0.0143 (0.0404)	0.0188 (0.0399)
SSI				0.7791*** (0.2442)			0.7736*** (0.2274)
Built-up area					-0.0148*** (0.0051)		
Distance						0.0114** (0.0044)	
AIC		491.583	490.985	487.062	487.367	489.356	486.946

* p<0.1, ** p<0.05, *** p<0.01; Std. error in brackets

Table 3. Linear effects, STAR model, southern transect (The second columns “Final” refers to the model specification including the spatial effect but no urbanization proxies; random effects included for crop and village scale.)

Variable	Factor	(1) Base	(2) Final	(3) SSI	(4) Built-up	(5) Distance	(6) SSI (no location effect)
Intercept		-0.1468 (0.3938)	-0.1563 (0.4162)	-1.4634** (0.6647)	-0.2495 (0.4193)	-1.5482** (0.6463)	-0.2945 (0.4624)
Household size		0.0294* (0.0177)	0.0271 (0.0180)	0.0280 (0.0177)	0.0286 (0.0179)	0.0303* (0.0176)	0.0303* (0.0178)
Soil quality	2: Middle Reference: Poor	-0.1118 (0.2252)	-0.1451 (0.2278)	-0.1438 (0.2280)	-0.1271 (0.2263)	-0.1155 (0.2279)	-0.0988 (0.2259)
	3: Very good	-0.0530 (0.2266)	-0.0665 (0.2284)	-0.0788 (0.2285)	-0.0528 (0.2274)	-0.0584 (0.2284)	-0.0425 (0.2272)
Slope	2: Moderate Reference: None	0.0915 (0.0818)	0.0910 (0.0822)	0.0745 (0.0826)	0.0910 (0.0814)	0.0693 (0.0826)	0.0889 (0.0822)
	3: Steep	0.0337 (0.0946)	0.0275 (0.0952)	0.0002 (0.0950)	0.0327 (0.0945)	-0.0010 (0.0948)	0.0294 (0.0949)
Car	Yes	-0.1844 (0.2050)	-0.1941 (0.2057)	-0.2213 (0.2085)	-0.1822 (0.2033)	-0.2147 (0.2087)	-0.1787 (0.2067)
Caste	2: SC Reference: General	0.0320 (0.1137)	0.0307 (0.1142)	-0.0233 (0.1242)	0.0665 (0.1115)	-0.0028 (0.1237)	0.0288 (0.1160)
	3: ST	0.2497 (0.1919)	0.2533 (0.1922)	0.2171 (0.1946)	0.2856 (0.1922)	0.2449 (0.1943)	0.2566 (0.1935)
	4: OBC	0.1956** (0.0903)	0.2084** (0.0917)	0.1869** (0.0902)	0.2164** (0.0916)	0.1870** (0.0893)	0.1905** (0.0904)
	5: None	0.1569 (0.3825)	0.1409 (0.3841)	0.2184 (0.3894)	0.1021 (0.3809)	0.2017 (0.3892)	0.1643 (0.3841)
	7: Other	0.3266 (0.4765)	0.3150 (0.4778)	0.3930 (0.4825)	0.2717 (0.4752)	0.3747 (0.4824)	0.3354 (0.4782)
Plot property	2: Rented Reference: Owned	0.0251 (0.1201)	0.0321 (0.1215)	0.0352 (0.1238)	0.0056 (0.1227)	0.0146 (0.1234)	0.0291 (0.1217)
	4: Gov. land (permission)	-0.0146 (0.2656)	0.0124 (0.2665)	-0.0808 (0.2725)	0.0298 (0.2629)	-0.0923 (0.2733)	-0.0323 (0.2680)
extension	Yes	0.1833* (0.1000)	0.1919* (0.1008)	0.1924* (0.1007)	0.1817* (0.0996)	0.1862* (0.1006)	0.1830* (0.1007)
dairy	Yes	0.1542 (0.2271)	0.1794 (0.2269)	0.2052 (0.2287)	0.1822 (0.2255)	0.2114 (0.2287)	0.1476 (0.2292)
Irrigation	Yes	0.2382* (0.1233)	0.2636** (0.1236)	0.2925** (0.1275)	0.2196* (0.1238)	0.2652** (0.1276)	0.2374* (0.1244)
Purpose	1: Marketing Reference: None of the others	0.1765 (0.1164)	0.1854 (0.1166)	0.2527** (0.1182)	0.1736 (0.1153)	0.2602** (0.1181)	0.1861 (0.1171)
	2: Exclusively fodder	-0.2836* (0.1506)	-0.2835* (0.1503)	-0.2674* (0.1514)	-0.2818* (0.1495)	-0.2677* (0.1511)	-0.2815* (0.1512)
	3: Fodder and Home consumption	0.1335 (0.1017)	0.1320 (0.1025)	0.0931 (0.1040)	0.1461 (0.1011)	0.0927 (0.1040)	0.1301 (0.1024)
Sowing season	1: Kharif 2015 Reference: Continuously	-0.0767 (0.2379)	-0.0692 (0.2385)	0.0700 (0.2442)	-0.1014 (0.2367)	0.0836 (0.2441)	-0.0440 (0.2427)
	2: Rabi 2015	0.1428 (0.1705)	0.1734 (0.1705)	0.2803 (0.1726)	0.1442 (0.1693)	0.2928* (0.1721)	0.1673 (0.1736)
	3: Summer 2016	0.0916 (0.1839)	0.1363 (0.1840)	0.2378 (0.1858)	0.1095 (0.1825)	0.2532 (0.1856)	0.1141 (0.1861)
	4: Kharif 2016	0.0677 (0.1706)	0.0968 (0.1707)	0.2036 (0.1732)	0.0677 (0.1695)	0.2134 (0.1726)	0.0908 (0.1735)
	5: Rabi 2016	0.1435 (0.1804)	0.1644 (0.1806)	0.2767 (0.1829)	0.1357 (0.1792)	0.2876 (0.1822)	0.1697 (0.1841)
number off-farm		-0.0804** (0.0383)	-0.0766** (0.0386)	-0.0829** (0.0385)	-0.0736* (0.0383)	-0.0814** (0.0383)	-0.0811** (0.0383)
SSI				1.7777** (0.7251)			
Built-up area					0.0070 (0.0052)		
Distance						0.0480*** (0.0180)	0.0045 (0.0084)
AIC		799.889	798.106	795.261	799.394	794.6	800.888

* p<0.1, ** p<0.05, *** p<0.01; Std. error in brackets

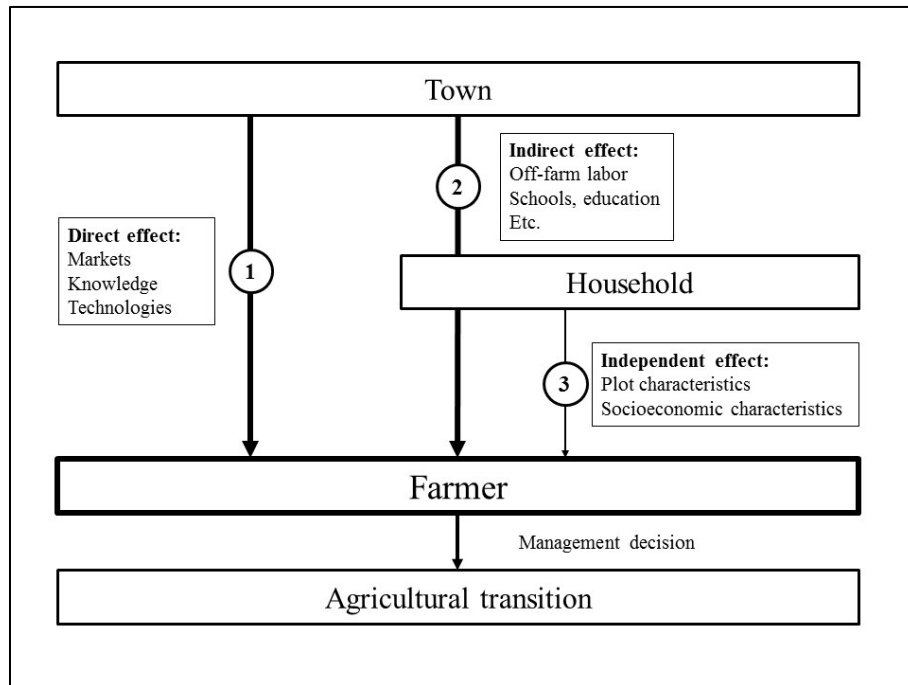


Figure 1. Outline of conceptual framework, urbanization effects on agricultural transition.

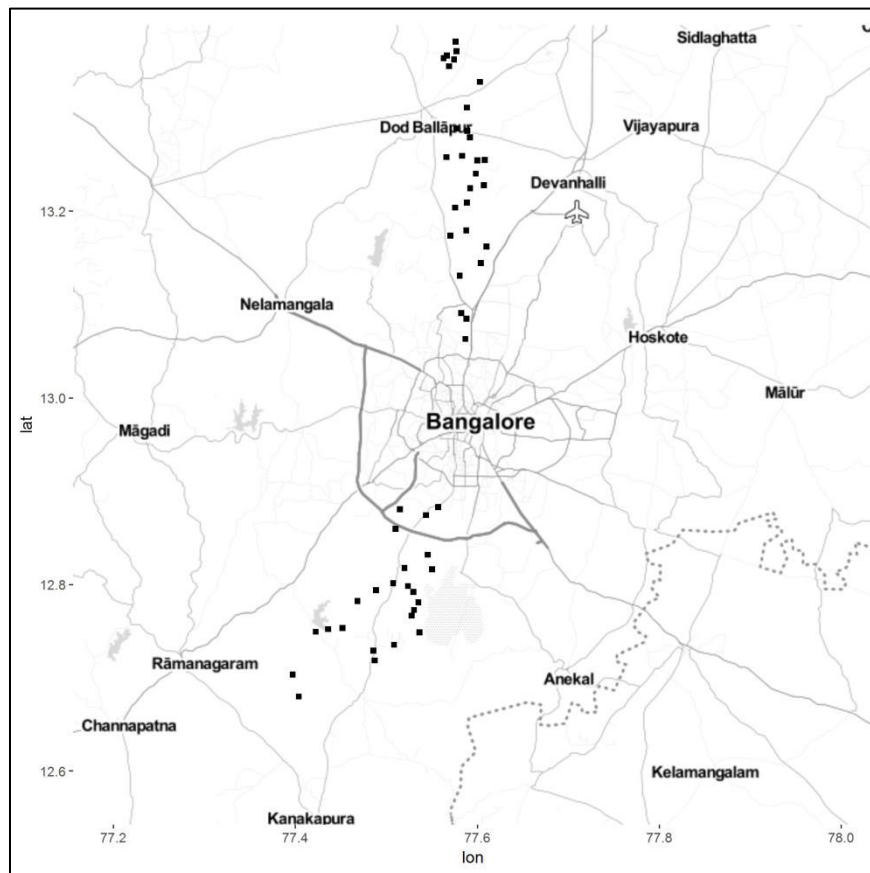


Figure 2. Location of villages in both research transects.

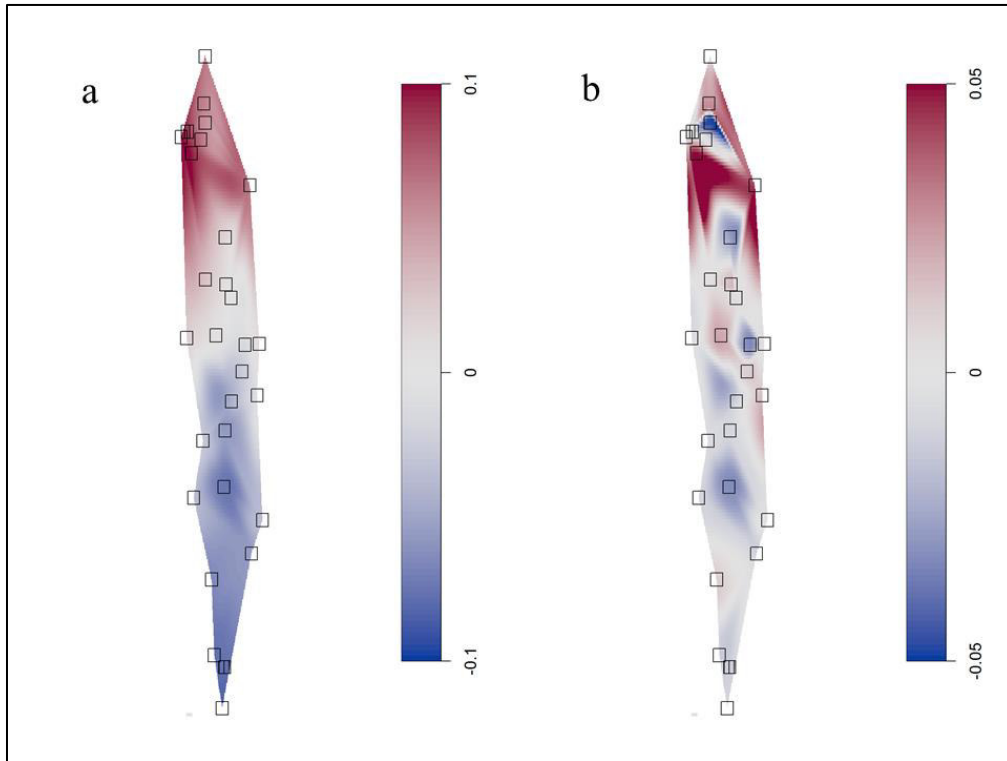


Figure 3. Location (a) and unstructured spatial (b) effect based on the final model, Northern transect (Table 2, column 2).

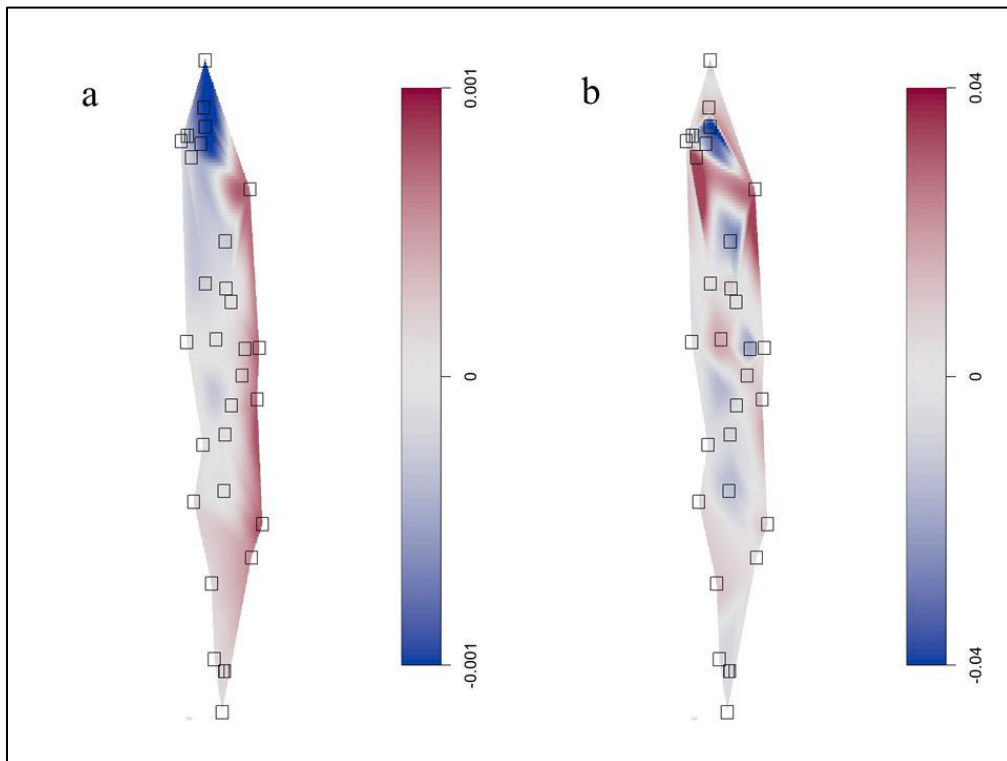


Figure 4. Location (a) and unstructured spatial (b) effect based on the SSI model, Northern transect (Table 2, column 3).

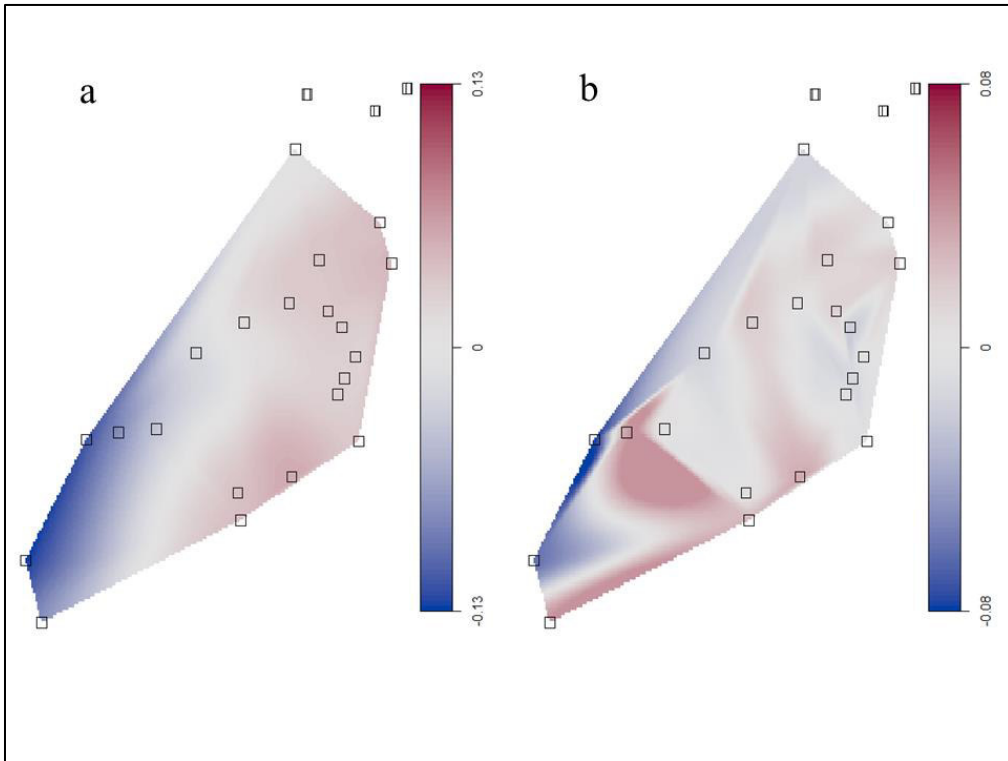


Figure 5. Location (a) and unstructured spatial (b) effect based on the final model, Southern transect (Table 3, column 2).

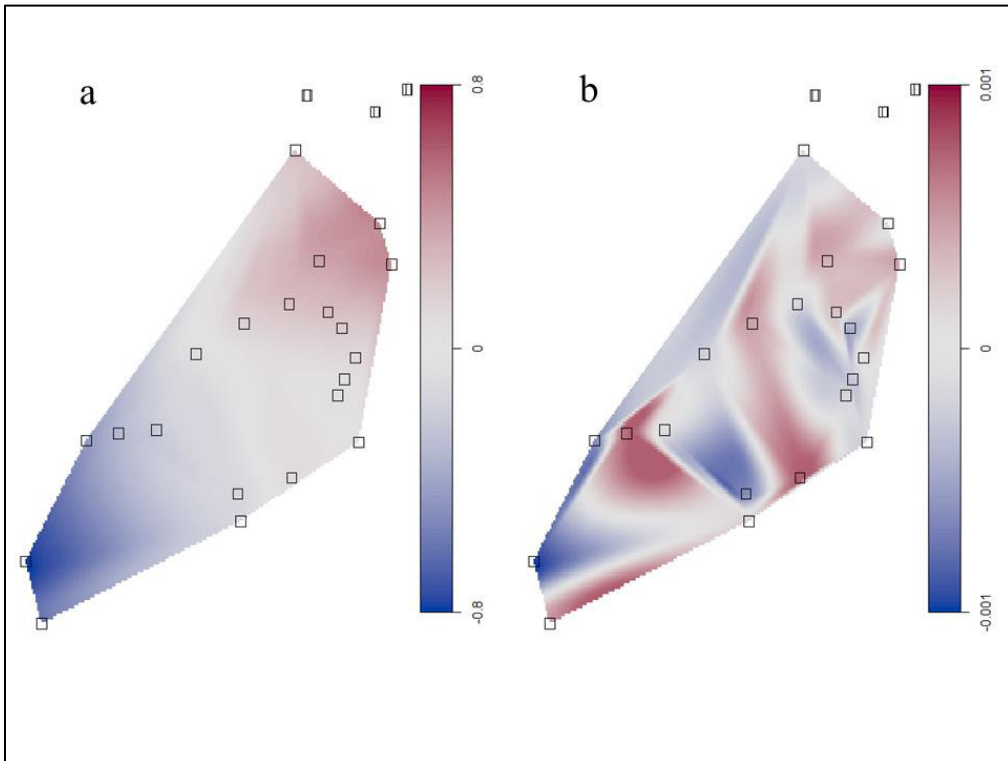


Figure 6. Location (a) and unstructured spatial (b) effect based on the Distance model, Southern transect (Table 3, column 5).