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Spatial Patterns of Rural Poverty in the São Francisco River Basin, Brazil

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Abstract

Information on the spatial distribution of poverty can be useful in designing geographically targeted rural poverty reduction programs. This paper uses recently released município-level data on rural poverty in Brazil to identify and analyze spatial patterns of rural poverty in the São Francisco River Basin (SFRB). Moran's I statistics are generated and used to test for spatial autocorrelation, and to prepare cluster maps that locate rural poverty "hot spots" and "cold spots." Research results demonstrate that rural poverty is spatially correlated in some parts of the SFRB, and where correlated, worse-off (better-off) *municípios* tend to be located next to worse-off (better-off) *municípios*. The policy implications of these results are discussed, as are proposed next steps in research.

1. Introduction

Despite the overall decline in the number of people living in poverty over the past 15 years, approximately 55 million individuals in Brazil remained poor in 2005. Based on the IPEADATA[1] database, the percentage of individuals considered poor in Brazil dropped from 42% in 1990 to 31% in 2005. Rural-to-urban migration has accompanied and perhaps fueled this decline in poverty, so with only about 20% of the poor living in rural areas today (FIPE et al., 2006), poverty in Brazil has become primarily an urban phenomenon. Still, the rural poor should not be neglected, particularly since they are so heavily concentrated in the Northeast of Brazil, where 70% (4.7 million) rural poor and 80% (1.8 million) of the extremely rural poor reside.[2]

In the SFRB, part of which lies in the Northeast of Brazil, the spatial distribution as well as the absolute number of rural poor stand out. In 2003, this basin contained 10% of all the Brazilian poor and 18% of all of the rural poor. In particular, of the approximately 17 million who inhabited the SFRB in that year, 21% were poor and of the

[1] This database can be browsed online at http:// www.ipeadata.gov.br.
[2] Throughout this paper we adopt the Azzoni at al. (2006) definitions of poverty and extreme poverty (or indigence). An extremely poor (or indigent) individual is one who belongs to a family with a per capita income that is insufficient to purchase the food required to meet him/her caloric needs, as defined by CEPAL (1996). A poor individual belongs to a household with a per capita income that is above the threshold required to meet his/her caloric needs, but less than 1.75 times this threshold amount.

over the 4 million people who lived in rural areas of the SFRB, nearly 1/3 were poor.[3] As seen in Figure 1, these rural poor were not evenly distributed across the basin. The proportion of the rural poor tended to be lower in the southern portion of the SFRB and much higher in the central northern zones, with some *municípios* registering rural poverty rates well above 50%. These parts of the basin also contain almost all of the rural population living in extreme poverty (Figure 2). Despite this general geographic pattern of rural poverty concentration, it is easy to identify less-poor *municípios* in the central and northern zones of the SFRB.

Figure 1. São Francisco River Basin: Percent Rural Population that is Poor, 2003

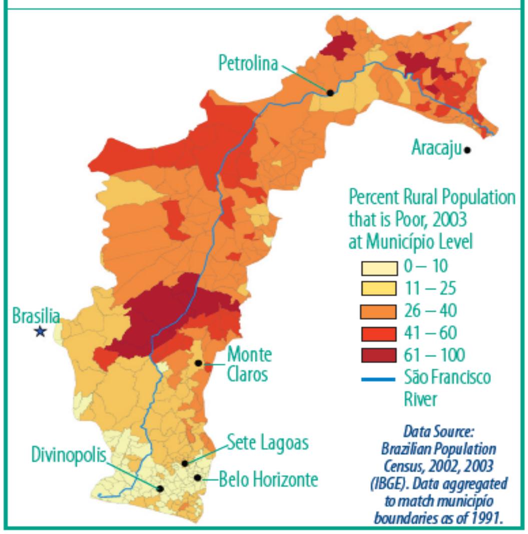
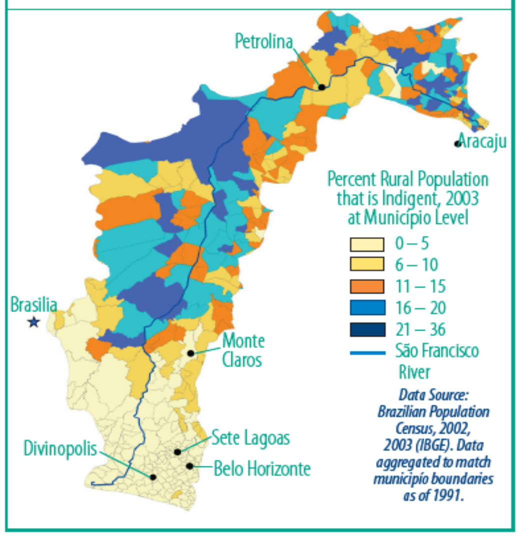


Figure 2. São Francisco River Basin: Percent Rural Population that is Indigent, 2003



Poverty reduction efforts are underway in Brazil and in the SFRB (e.g., *Programa Fome Zero, Bolsa Escola, Bolsa Alimentação, Cartão Alimentação e Auxílio Gás*) and are having effect (FAO 2006). But in areas such as the SFRB with marked intra-regional income disparities, rural poverty programs might benefit from more and more detailed information on the spatial distribution of poverty (Minot et al. 2006), especially if reliable links could be established between poverty and easily-observable variables (e.g., access to water). To date, however, Azzoni et al. (2006) provide the only recent spatially disaggregated data on rural poverty in Brazil. Since these data are provided at *município*

[3] The total rural population of 4 million refers to the Brazilian Demographic Census of 2000. This is the most recent year for which separated estimates exist of rural and urban population at *município* level. For this paper, all rural poverty rates are based on the number of rural poor in 2003 divided by the total rural population in 2000.

level, it is possible to select the set of *municípios* within the boundaries of the SFRB[4] and construct maps (e.g., Figures 1 and 2) that allow researcher and policymakers to see the distribution of rural poverty across the basin. Such maps are important points of departure, but they leave unanswered key questionings, e.g., can we statistically confirm the spatial patterns that the poverty maps present to us? More specifically, are there rural poverty "hot spots" in the area, i.e., sub-regions within the SFRB that may have fallen into poverty traps? Or, might there be rural poverty "cold spots" that have successfully escaped poverty and that could provide strategies for doing some more generally in the SFRB?

Information on spatial patterns of rural poverty in the SFRB may also shed light on the importance of location as a causal factor *per se*.[5] Location may be important because geographical spillovers of human capital, physical infrastructure, or knowledge and information in a given *município* may affect the poverty levels of its rural neighbors. Spatial interdependence of rural poverty may also occur because of often unobserved factors such as soil quality, topography, and climate.

Our main goals in this paper are to use recently released data on rural poverty at *município* level to describe spatial patterns of rural poverty in the SFRB by constructing poverty maps, to calculate a Moran's I spatial autocorrelation index of rural poverty (Sections 2 and 3), and in Sections 4 to use cluster analysis to identify rural poverty "hot spots" and "cold spots." In Section 5 we discuss how rural poverty reduction programs in the SFRB might be redesigned to be more effective, and present next steps in research.

2. Spatial Autocorrelation of Rural Poverty in the SFRB – The Moran's I

The main question addressed in this section is whether the *observed* pattern of rural poverty across the SFRB as seen in Figures 1 and 2 is as likely as any other spatial pattern. If we discover, for example, that poor (rich) *município*s tended to be surrounded by poor (rich) *município*s, or vice-versa, this would indicate there was *positive* spatial autocorrelation among the rural poor across the basin. If, on the other hand, we find that poor (rich) *município*s tended to be surrounded by rich (poor) *município*s, we would then

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[4] See Torres et al. (2006) for an explanation of how municipios 'falling within' the SFRB were identified.

[5] Some recent examples of studies on the link location and poverty are Besley, and Burgess, 2000, Traxler and Byerlee, 2001, Amarasinghe et al., 2000, and Palmer-Jones and Sen, 2006.

say there was *negative spatial* autocorrelation among the rural poor across the basin. Or, there may have been no spatial correlation at all.

We begin by defining a proportional measure of rural poverty, i.e., the proportion of the rural population that was poor (p) in each *município i*, given by

$$(1) \qquad p_i = \frac{n_i}{x_i}\,,$$

where n_i is the total number of rural poor in *município i*, and x_i is the total rural population in *município i*, with $i = 1,\ldots,N$.

To measure spatial autocorrelation, we use the global Moran's *I* statistic (Moran 1948, Anselin 1996, Cliff and Ord 1981, Pinkse 2003, and Griffith 2003), given by

$$(2) \qquad I = \frac{\sum_{i,j} w_{ij}\,(p_i - \bar{p})(p_j - \bar{p}) / \sum_{i,j} w_{ij}}{\sum_i (p_i - \bar{p})^2 / N}\,.$$ [6]

where (p_i) is rural poverty rate in *município i*, $\bar{p} = \frac{\sum_i p_i}{N}$ is the average rural poverty rate over the entire SFRB, and (p_j) is the rural poverty rate in *município j*. The term $(p_i - \bar{p})(p_j - \bar{p})$ is an element of a poverty rate values matrix, with the poverty rates standardized around the sample mean, and w_{ij} is a element of a spatial weighting matrix. If *município i* shares a common boundary with *município j*, then $w_{ij} = 1$, otherwise $w_{ij} = 0$. This definition of neighboring areas is based on *rook contiguity*. The Moran's I statistic can be compared to the Durbin-Watson statistic used to detect autocorrelation in time-series data.

In this application the weighting matrix is row-standardized, in which the weights are defined as $w_{ij}^s = \frac{w_{ij}}{\sum_j w_{ij}}$, such that $\sum_j w_{ij}^s = 1$. For example, if a *município i* has 4

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[6]In the numerator of *I*, $\sum_{i,j} w_{ij}\,(p_i - \bar{p})(p_j - \bar{p})$, is a gamma statistic with (p_i) and (p_j) as the random variables, and as such, it is scale-dependent. In order to make it scale-independent, we divide it by $\sum_{i,j} w_{ij}$ and by a consistent estimator of the variance of the poverty rate (p_i), $\sum_i (p_i - \bar{p})^2 / N$.

neighbors, $w_{ij}^s = 1/4$. The row standardization has two implications: 1) it implies equal weights across neighbors of a same *município*, and 2) it implies that the sum over all elements of the row-standardized weight matrix (w_{ij}^s) is equal to the total number of observations (*N*); that is, in (2), $\sum_{i,j} w_{ij} = N$.[7] Therefore, (2) can be re-written as

$$(2') \qquad I^s = \frac{\sum_{i,j} w_{ij}^s (p_i - \overline{p})(p_j - \overline{p})}{\sum_i (p_i - \overline{p})^2}.$$

If *município*s with above-average (below-average) poverty rates are surrounded by neighboring *município*s with above-average (below-average) poverty rates, the cross product term $(p_i - \overline{p})*(p_j - \overline{p})$ becomes positive, making $I^s > 0$, and implies that there is positive spatial autocorrelation. On the other hand, if *município*s with above-average (below-average) poverty rates are surrounded by neighboring *município*s with below-average (above-average) poverty rates, the cross product term $(p_i - \overline{p})*(p_j - \overline{p})$ is negative , making $I^s < 0$, and implying that there is negative spatial autocorrelation. The closer I^s gets to zero, the weaker the evidence to support spatial autocorrelation.

The value of I^s calculating using (2') for all *municípios* of the SFRB is equal to 0.72, which is greater than zero and strongly suggests a positive spatial autocorrelation of rural poverty.[8] Although statistical significance remains to be confirmed, this number suggests that for the SFRB, there are more *municípios* with high (low) rural poverty rates surrounded by *municípios* with high (low) rural poverty rates than would be the case if poverty were distributed randomly.[9] It also indicates that poverty in the SFRB is

[7] With row standardization, the sum of weights in each row becomes 1. Since there is one row for each município in the sample, there are *N* rows. Therefore, the sum over all weights in the matrix, $\sum_{i,j} w_{ij}$, is N.

[8] GeoDa™ is used to calculate all statistics and clusters maps in this paper. This software was developed by the Center for Spatially Integrated Social Science (CSISS) at the University of Illinois, Urbana-Champaign, Urbana, IL, USA.

[9] In fact, rural poverty rates are positively spatial autocorrelated for 90% of the *municípios* in the SFRB; 42% are 'low-low', that is, they have below-average rural poverty rates and are surrounded by *municípios*

spatially distributed in clusters, which is compatible with the visual images of the spatial distribution of poverty depicted in Figures 1 and 2, and the notion of contagion or diffusion which suggests that as poverty in one *município* increases, the likelihood of poverty in its neighbors increases as well (Anselin, 1992). However, this basin-wide statistic does not tell us <u>where</u> these rural poverty clusters might be, but rather only suggests that the spatial pattern of poverty that we observe is not random -- there is more similarity by location than if the pattern were random.

3. Statistical Inference and the Empirical Bayes Index of Spatial Autocorrelation

Although 0.72 suggests positive spatial autocorrelation of rural poverty, statistical inference analysis is required to statically confirm this against the null hypothesis of spatial randomness (Ho: $I^s = 0$). To test for the statistical significance of I^s, we use an inference procedure based on a permutation approach, in which I^s is recomputed for a large number of re-sampled sets of *município*s. In each permutation, a p_i is held fixed (not used in the permutation) and the remaining poverty rates are re-allocated randomly to the different *município*s. For each re-allocation a value for I^s is computed. After a given number of permutations, a distribution of I^s values is drawn, and a mean and a variance are calculated. This distribution is often called the *reference* or *null* distribution (Assunção and Reis, 1999).

One possible problem associated with the permutation approach is that it assumes that any permutation of rural poverty values (p_i) is equally likely to occur among the (N) *município*s. However, if total rural population differs considerably among the different *município*s, those with smaller populations will be more likely to assume extreme values. In other words, the variance of p_i may not be constant across *municípios* and it may in fact increase as the population decreases. As pointed out by Besag and Newell (1991), when this is the case, the null distribution for I^s is inaccurate.[10]

that have below-average poverty rates; 48% are 'high-high', that is, they have above-average rural poverty rates and are surrounded by *municípios* that have above-average poverty rates.

[10] Consider, for instance, two *municípios* (A and B) that are equally poor (say with poverty rates of 50%), and that in location A there are four individuals and in B there are six individuals. Poor individuals are labeled **P,** and the non-poor are labeled **Np**. If 2 individuals are randomly select from location A, you could draw a sample containing the two poor individuals (PP) and conclude that the poverty rate was 100%, or you could draw one poor person and then one non-poor person (PNp) and conclude that the poverty rate

We follow Assunção and Reis (1999), who propose to fix this problem by adjusting the global Moran's *I* as defined in (2') and correct for the variance instability. Under their approach, ($p_i - \bar{p}$) in (2') is replaced by ($z_i - \bar{z}$), where

$$(3) \qquad z_i = \frac{p_i - b}{\sqrt{v_i}},$$

and $\bar{z} = \frac{\sum_i z_i}{N}$. In ($z_i$), $b = \frac{\sum_i n_i}{\sum_i x_i}$, n_i is the total number of rural poor individuals in *município i*, and (x_i) is the total rural population in *município i*. $v_i = a + \frac{b}{x_i}$, in which $a = s^2 - \frac{Nb}{\sum_i x_i}$, and $s^2 = \sum_i \frac{x_i(p_i - b)^2}{\sum_i x_i}$. Notice that the variance (v_i) and the mean (b) are both based on the observed values of population and poverty rates. Notice also that v_i now increases as the population x_i decreases. By using ($z_i - \bar{z}$), we then redefine (2') and calculate the so-called *EBI* - Empirical Bayes Moran's I (Assunção and Reis, 1999), which in the version with the row-standardized spatial weighting matrix becomes:

$$(4) \qquad EBI^s = \frac{\sum_{i,j} w_{ij}^s (z_i - \bar{z})(z_j - \bar{z})}{\sum_i (z_i - \bar{z})^2}.$$

The next step is to calculate EBI^s for the SFRB and use the permutation approach to generate a null distribution, which will then allow us to test for the statistical significance of measured spatial autocorrelation. We first calculate z_i for each of the *município*s, and then $\bar{z}$. By plugging these values into (4), we find EBI^s of 0.83, which

was 50%, or a non-poor individual and then a poor one (NpP) and calculate the same 50% rural poverty, or, finally, you could select two non-poor individuals (NpNp) and calculate a rural poverty rate of zero. So, there is a 50% chance of getting the extreme values of 0 and 100% rural poverty. If the same exercise is performed in location B that is comprises of three individuals, the odds of getting extreme values of rural poverty are lower. More specifically, there are eight possible combinations: PPP (100% poor), PPNp (66% poor), PNpP (66% poor), PNpNp (33% poor), NpPP (66% poor), NpPNp (33% poor), NpNpP (33% poor), NpNpNp (0% poor). In more populated location B, the chances of getting the extreme values of zero and 100% rural poverty drops to half, 1/8 + 1/8 = 25%, as compared with the less-populated location A.

confirms the positive spatial autocorrelation of rural poverty rates among the *municípios* of the SFRB.

The permutation procedure was performed 10,000 times by redistributing the vector of adjusted rural poverty values ($z_1, z_2, z_3, \ldots, z_N$). Each time the z_i values were redistributed, a value for EBI^s was calculated. The *p*-value was calculated as the proportion of times the value of EBI^s exceeds 0.83. According to these calculations, the EBI^s value of 0.83 was statistically significant at the 5% level of significance, with a standardized Z-value of 25.9 and a *p*-value = 0.0001.[11] This *p*-value was computed as $\frac{M+1}{R+1}$, where R is the number of permutations and M is the number of the statistic computed from the permutations was equal to or greater than 0.83. [12]

An EBI^s value of 0.83 compared with our initial calculation of Moran's I, I^s, of 0.72, indicates that the spatial correlation between rural poverty rates in *município i* and neighboring *municípios* is stronger when rates are standardized as in (3) and the variance instability is reduced. Hence, increasing the precision with which rural poverty is measured will likely increase the spatial correlation among rural poverty rates in the SFRB.

4. Local Indicators of Spatial Association (*LISA*) and Clusters of Rural Poverty

Although a Moran's I of 0.83 clearly demonstrates that the spatial distribution of rural poverty in the SFRB is not random, it does not locate poverty clusters. We turn to local indicators of spatial association or *LISA* (Anselin, 1995) for this task. *LISA* is a class of statistics that provides location-specific information (by *município,* in this case) and estimates the extent of spatial autocorrelation between the value of a given variable (in our case, rural poverty rate) in a particular location and the values of those same variables in locations around it. Through inference analysis we are able to identify spatial clusters of rural poverty, or rural poverty 'hot-spots' (high-poverty *municípios* surrounded by

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[11] Where $Z = \frac{I^s - E[I^s]}{\sqrt{VarI^s}}$. For the derivation of the first and second moments of I^s, see Cliff and Ord (1981).

[12] Since the p-value depends on the number of permutations, it is often called pseudo p-value.

high-poverty *municípios*) and/or 'cold-spots' (low-poverty *municípios* surrounded by low-poverty *municípios*). These clusters might be comprised of a single *município* and its contiguous neighbors, or a larger set of contiguous *municípios* for which the *LISA* values are statistically significant. We use the Local Moran's *I* statistic or *LMI*, one of several statistics that falls within the *LISA* definition.[13] It is defined as follows:

$$(4) \qquad LMI_i = \frac{x_i}{\sum_i x_i^2} \sum_j w_{ij} x_j ,$$

where, $x_i = p_i - \bar{p}$ and $x_j = p_j - \bar{p}$, and p_i and p_j are, respectively, the rural poverty rates for *municípios* i and j, and $\bar{p}$ is the sample mean. Spatial weights, w_{ij}, are defined as before: $w_{ij} = 1$ if the i and j municípios are contiguous neighbors, $w_{ij} = 0$ otherwise, based on *rook contiguity*.

Analogous to the Global Moran's *I*, positive values of *LMI* indicate positive spatial autocorrelation, i.e., that a given *município* is surrounded by *municípios* with similar rural poverty rates, either above or below the basin-wide average. On the other hand, negative values of *LMI* indicate negative spatial autocorrelation, i.e., that a given *município* is surrounded by *municípios* with dissimilar rural poverty rates. If rural poverty is negatively spatially correlated, either a given *município* with an above-average rural poverty rate is surrounded by neighbors with below-average rural poverty rates, or vice-versa.

We now turn to statistical inference of *LMI*. To do so, we use the same procedure employed to test for the significance of the Global Moran's *I*. That is, we use the permutation approach in which observed rural poverty rates are randomly re-assigned to each of the *municípios*. Each time a permutation is performed, a set of *N LMI*s is calculated; a null distribution for the *LMI* is constructed and is then used to test for the statistical significance of the observed *LMI*. We also take into account that the variance of p_i is not constant across *municípios* with different total rural populations, and follow Assunção and Reis (1999) to adjust the *LMI* in (4) by substituting $z_i - \bar{z}$ for x_i, where z_i

[13] See Anselin (1995) for examples of other *LISA* statistics, such as the *Local Geary*.

and $\bar{z}$ are defined as in Section 3. *LMI* is then redefined as *LEBI* or Local Empirical Bayes Moran's *I*, (Anselin, 2005):

$$(5) \qquad LEBI_i = \frac{z_i - \bar{z}}{\sum_i (z_i - \bar{z})^2} \sum_j w_{ij}(z_j - \bar{z})$$

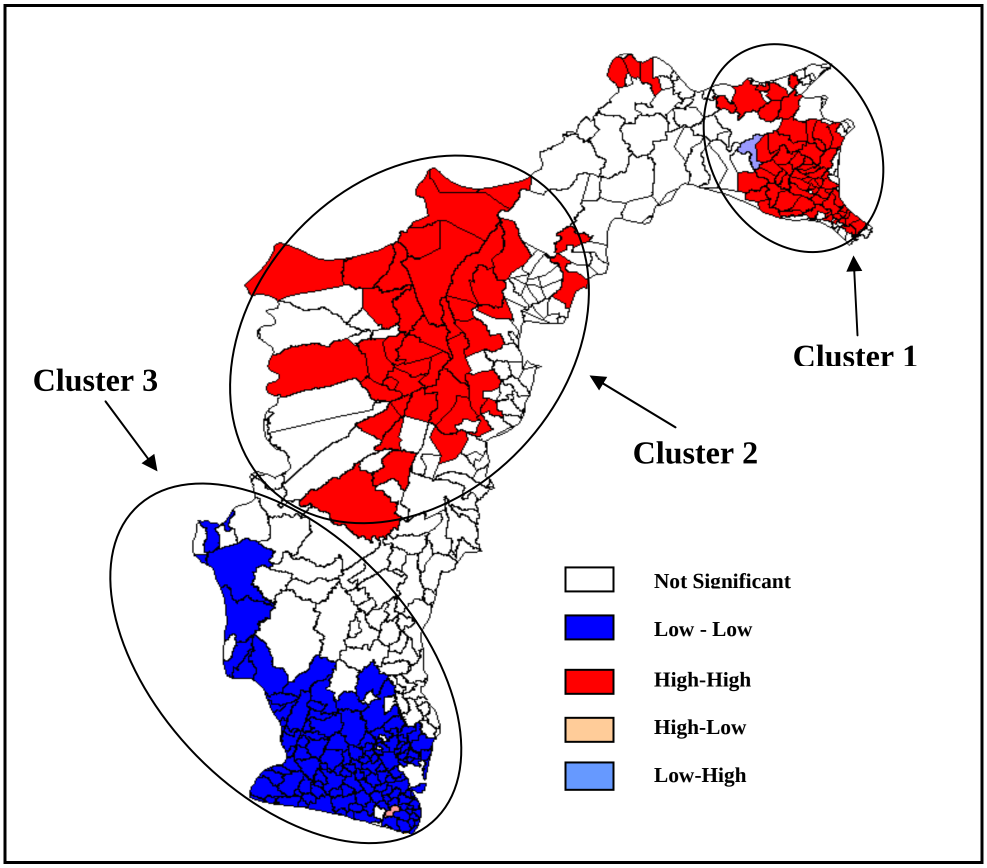
Figure 3 depicts the *municípios* with statistically significant *LEBI*, using a significance level of 0.05. We can identify 3 main clusters of rural poverty in the SFRB. Clusters 1 and 2 are rural poverty 'hot-spots' and correspond to positive, and high-high spatial autocorrelation, indicating spatial clusters of *municípios* with above-average rural poverty rates. Cluster 3 is a 'cold-spot' and also corresponds to a positive, but low-low, spatial autocorrelation, indicating a spatial cluster of *municípios* with below-average rural poverty rates. This clearly suggests that there are two spatial autocorrelation patterns of rural poverty values in the São Francisco River Basin. These patterns of rural poverty clustering are different from those based on total poverty (urban and rural) in the same geographic area (Torres et al. 2006). Among other differences, many more clusters of *municípios* displaying negative autocorrelation (high-low and low-high municípios) were identified when total poverty data were used.

These clusters of rural poverty may be attributable to spatial spillovers of, for example, human capital, physical infrastructure, knowledge and information, soil quality, topography, climate etc., that can cause poverty in one *município* to affect poverty in its neighbors, and vice-versa. Although there are obvious candidates for factors that may keep these clusters equally poor (non-poor), such as the lack of irrigation infrastructure in the semi-arid region (which characterizes Cluster 2), or the relatively larger endowments of human capital, agricultural R&D, nearness to major markets (which generally characterize the sub-region occupied Cluster 3), or the extremely low and erratic rainfall and stagnated agriculture systems (which generally characterize the area included in Cluster 1), further analysis is required to determine the causes of these spatial patterns of rural poverty in the SFRB.[14] Multivariate regression analysis using the appropriate

[14] Many studies have examined the determinants of rural poverty in different socioeconomic and agroecological contexts. See, for example, Finan et al., 2005; Han, 2005; Rozelle et al., 2005; Hussain and Hanjra, 2004; Besley and Burgess, 2000; Fan et al., 2000; Gunning et al., 2000; Scott, 2000; Zhang, 2000; Blackden and Chitra, 1999; Carter and May, 1999; Dollar and Kraay, 2000; Datt and Ravallion, 1998;

econometric techniques that take account of spatial interrelationships among poverty rates and also among the variables that may explain poverty is the proper analytical approach.

Figure 3 – Local spatial clusters of rural poverty in the São Francisco River Basin



5. Conclusions and Next Steps

In this paper, we use *município*-level data to identify and analyze spatial patterns of rural poverty in the São Francisco River Basin (SFRB) in Brazil. We found that rural poverty is spatially autocorrelated in the SFRB – i.e., observed spatial patterns of rural poverty are not likely to be random. More specifically, our results indicate a positive spatial autocorrelation of rural poverty in the SFRB; *municípios* with above-average levels of rural poverty tended to be surrounded by similarly poor *município*s, and

World Bank, 1998; Grootaert et al., 1997; Reardon and Taylor, 1996; Binswanger et al., 1995; and Reardon and Vosti, 1995.

municípios with below-average levels of poverty (likewise) tended to be surrounded by similarly better-off *municípios*.

Looking more deeply into the local patterns of the spatial distribution of rural poverty, we discovered that *municípios* of the SFRB belonging to Cluster 1 (mainly in the northeastern states of Sergipe and Alagoas in the lower portion of the basin), and to Cluster 2 (mainly northern Minas Gerais and western Bahia) were more likely to have high levels of rural poverty. On the hand, *municípios* in the southern portion of the SFRB (those located in relatively high-rainfall areas and closer to large urban centers of Brasília or Belo Horizonte) were more likely to have low levels of rural poverty. Overall, more than 50% of the *municípios* in the SFRB belonged to one of these three poverty clusters. Roughly half of these *municípios* were in the Clusters 1 or 2, where *municípios* with above-average poverty rates were surrounded by *municípios* with above-average poverty rates.

Our results indicate that poverty reduction policies in the SFRB should take into account the spatial distribution of poverty. Not only is poverty in the SFRB clustered spatially, but the bulk of the basin's poor resides in *municípios* that comprise the poverty 'hot spots' we identified. These clusters of *municípios* that comprised poverty 'hot spots' did not correspond to state-level boundaries (the political delineations often used to measure poverty and to manage poverty reduction programs), so scope may exist for geographically refocusing poverty reduction efforts to make them more efficient. Moreover, our analysis suggests that for one or more reasons, poverty in one *município* is affected by (or affects) poverty in neighboring *municípios*, perhaps in predictable ways; this information, too, may help make rural poverty alleviation efforts more effective and efficient.

These results set the stage for identifying factors that influence rural poverty in the SFRB, factors that may themselves be spatially correlated. Therefore, our next step is to undertake multivariate spatial econometrics to investigate, among other things: 1) what agroecological factors (e.g., rainfall, topography, soil type) are linked to rural poverty, and if any are linked, how should poverty reduction programs in the SFRB be modified to take these links into consideration? 2) Why are rural poverty clusters 1 and 2 not contiguous? Are there structural differences between them? What is different about the geographic area that separates these two clusters? 3) Are there other statistically significant types of spatial dependence of rural poverty in the basin, such as spatial error dependence, and how does one take account of such potential differences analytically?

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