

## Examining transport needs in the Global South using a screening framework

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### Abstract

Despite the increasing emphasis on the social aspects of transport externalities in the global agenda of public policies (UN, 2016), transport appraisals (ex-ante) are still strongly driven by economic and environmental analysis only (Geurs et al, 2009; Jones and Lucas, 2012). In this context, the goals targeting poverty reduction and social well-being promotion become fundamentally undermined when the social impacts are overlooked in the decision-making process of transport development (Vasconcellos, 2003; World Bank, 2006; Jones and Lucas, 2012, Jones et al, 2013).

Hence, in a context where the transport-related needs have been either disregarded, not fully captured, or addressed by subjective approaches, the proposition of an objective and well-grounded screening framework of transport needs can play a pivotal role in making transport planning more socially inclusive. The framework that is proposed applies the Analytic Hierarchy Process (AHP) and spatial autocorrelation techniques to provide tools and evidence-based guidelines that can guide transport interventions in Northeast Brazil to become more effective in reducing poverty. While the socially driven framework that is outlined here focuses on the transport needs of Northeast Brazil, it can also be replicated in other developing countries facing similar socio-economic and transport challenges. The results show that different regions of Northeast Brazil suffer differently from externalities and that sub-regional analysis is needed.

### Introduction and background

The methodologies applied to screen regional transport needs and prioritise transport interventions in Brazil have persistently neglected fundamental aspects of poverty reduction and the social dimension of transport (Benevenuto and Caulfield, 2019). Dalbem and Brandão (2010) report that the Brazilian federal guidelines for road transport appraisal are poorly detailed and are restricted to economic and environmental evaluations. Moreover, Paranaíba (2017) states that even for screening urban mobility needs, the Federal Guidelines fall short in defining clear criteria for the selection of potential transport projects.

Beyond the Brazilian case, several authors have asserted that poverty reduction and social issues are, in general, still superficially addressed in transport appraisals, and more interdisciplinary research is needed to develop tools and call attention to the social dimension in the decision-making process (Geurs et al 2009; Van Wee and Geurs,

2011). Overall, these studies also reinforce the latent need for an objective method of screening the transport needs at a municipal and regional that can objectively guide transport interventions to where and for whom they are most needed.

Geurs et al. (2009) argue that traditional transport appraisal frameworks like Cost-Benefit Analysis (CBA) often underexpose the social dimension claiming an alleged lack of objectivity and a difficulty to precisely estimate the social effects of transport projects and policies. In terms of transport modelling, Vasconcellos (2003) argues that traditional models, such as the four-stage model, should not be enhanced, but rather fully replaced by novel social and political approaches that are able to carefully address issues relating transport, equity and poverty reduction. Furthermore, policy recommendations reported in the academic literature and by numerous international guidelines have consistently emphasised the essential role of accessibility audits when appraising transport interventions in terms of distributional effects, equity and social exclusion (Thomopoulos et al, 2009; Mackie and Worsley, 2013; Pereira, 2019).

Nonetheless, since accessibility alone does not account for all the aspects in which transport impacts poverty and well-being, a more comprehensive socially driven framework is still needed. tackling the cycles of poverty through transport development requires strategies to address all the eight Transport-Related Exclusion (TRE) dimensions. Despite the importance of performing accessibility assessments in these contexts, other TRE dimensions also need to be evaluated. Thus, by clarifying what and where the priority transport-related needs are, the decision-making process can have the right inputs to be more objective and effective in reducing poverty.

The definition by Geurs et al. (2009) for the social impact of transport is used in this research as the positive/negative influence that transport-related interventions have on well-being, preferences, behaviour or perception of individuals, groups, social categories and society in general. It is worth mentioning that in order to avoid the risk of neglecting important issues related to poverty reduction, this definition might occasionally overlap with economic and environmental impacts.

Table 1 summarises a substantial amount of research reported in academic literature (Vasconcellos, 2003; Geurs et al, 2009; Jones and Lucas, 2012; Jones et al, 2013; Mackie and Worsley, 2013) as well as international guidelines (DNIT, 2006; World Bank, 2006; Eliasson, 2013; TaIC, 2016; Marcelo and House, 2018) applied in several countries to measure transport impacts on social exclusion, multi-dimensional poverty and equity. The table presents theoretical concepts that underpin the social effects of transport interventions.

For the sake of clarity, five categories and twenty-three subcategories are used based on the literature to classify all these dimensions of measurable social effects. Table 1 also presents some specific examples that have been applied in the literature to disaggregate and measure these subcategories. Additionally, a corresponding TRE dimension (Church et al, 2000; Benevenuto and Caulfield, 2019) is linked to each subcategory in order to exemplify how these dimensions can be measured by usual proxies. However, Lucas (2012) states that while these TRE dimensions provide an overall description of the nexus between social exclusion and transport, they fail in identifying where transport policy attention should be focused. This paper attempts covers this research gap by developing a framework that can evaluate where and which transport-

related needs should receive higher attention in social appraisals of transport interventions. Our work builds upon the seminal work of Lucas (2012) and shows how the screening method can provide meaningful insights into the equity impacts of transportation.

**Table 1: Summary of transport impacts on poverty**

| Category           | Sub-category                         | Example of Disaggregation                                                                                                | Transport-related exclusion dimensions |
|--------------------|--------------------------------------|--------------------------------------------------------------------------------------------------------------------------|----------------------------------------|
| Accessibility      | To Education                         | Public/Private and Primary/Secondary/Training/Higher                                                                     | From facilities                        |
|                    | To Healthcare                        | Public/Private and GP's/Clinics/Hospitals                                                                                | From facilities                        |
|                    | To Employment, and social activities | Rural (to urban centres), Urban (jobs, gatherings, supermarkets)                                                         | From facilities                        |
|                    | To Transport network                 | Rural (all-season roads), Urban (public transport nodes)                                                                 | Geographic                             |
|                    | At a meso-level                      | Between neighbourhoods (mostly for social trips)                                                                         | Geographic                             |
|                    | At a micro-level                     | Facilities adapted to special needs (people with disabilities, elders, etc)                                              | Physical                               |
| Economic           | Land                                 | Land use, land and rent price, densification, agglomeration                                                              | Economic                               |
|                    | Productivity                         | Employments changes estimates, increase in production                                                                    | Economic                               |
|                    | Affordability                        | Public transport (fares) and Private transport (vehicle operating costs)                                                 | Economic                               |
| Social environment | Severance                            | By physical barriers or intense traffic during the construction of operation                                             | Spatial                                |
|                    | Discrimination                       | Prevention of movement based on gender, race, ethnicity, etc                                                             | Social position-based                  |
|                    | Security                             | Crime prevention measures (CCTV, lighting, emergency call, etc)                                                          | Fear-based                             |
|                    | Forced Relocation                    | Uncertainty of being relocated and relocation itself                                                                     | Fear-based, Geographic                 |
| Transit-related    | Travel time                          | Time savings in all types of trips (business, leisure, educational, etc)                                                 | Time-based                             |
|                    | Reliability                          | Frequency, timetables, opening and closing times of public transport.                                                    | Time-based                             |
|                    | Comfort                              | Levels of crowdedness and stress during the trips                                                                        | Physical                               |
|                    | Resilience                           | Disruption of service/infrastructure due to floods, landslide, accidents, etc                                            | Indirectly related to all dimensions   |
| Health-related     | Water pollution                      | During operation (waterways) and construction (groundwater, rivers)                                                      | Idem                                   |
|                    | Air quality                          | Increased risk of death/diseases due to high exposure to CO <sub>2</sub> , NO <sub>x</sub> , SO <sub>2</sub> , particles | Idem                                   |

|  |                  |                                                                            |      |
|--|------------------|----------------------------------------------------------------------------|------|
|  | Noise            | During construction and operation (noise nuisance, sleep disturbance, etc) | Idem |
|  | Vibration        | Due to vehicles (operation) and machines (construction)                    | Idem |
|  | Accidents        | Fatal, serious, slight, damage only, or including dangerous cargo          | Idem |
|  | Physical fitness | Change in premature death by increasing the use of NMT                     | Idem |

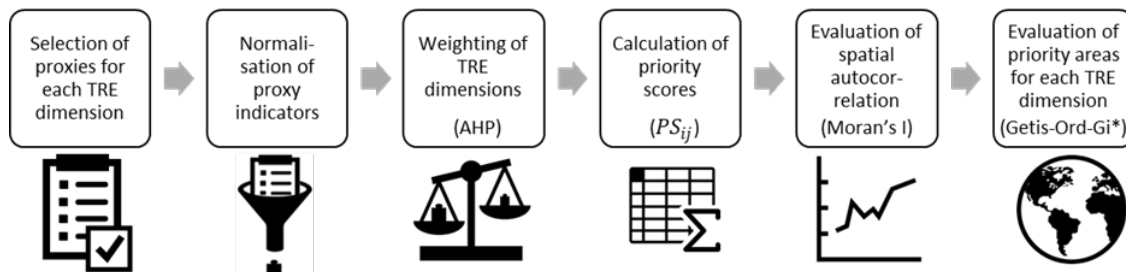
This paper is divided as follows; methodology describing the reasons for the selected data and techniques; the resulting maps and graphs along with a discussion and interpretation of the findings; and, finally, the conclusion reflecting on policy implications and guidelines devised from this study.

Our research makes a strong contribution in the field of examining the geographical impacts of transport and policy analysis. The research examines how transport infrastructure interventions impact upon the economy, spatial development and livelihoods.

Our approach adds to the previous frameworks in this field by proposing a tailored transport screening framework capable of performing a transparent and objective analysis of the social dimension that can complement mainstream transport planning techniques in Northeast Brazil, and pointing out the lines of actions that are most needed at a local and regional level to target poverty through transport development more effectively. It takes the main tenants of the previous frameworks in this field but by examining outcomes in isolation, it enables a deeper interpretation of policy interventions.

## Methods

The screening framework that is proposed converts open access data into maps showing where and what are the transport needs that should be prioritised by future transport interventions. Figure 1 presents a schematic overview of the steps taken throughout this process. Further rationale for each step is given in this section, describing the techniques and the input data that have been applied to each step.



**Figure 1: Overall methodology of the screening framework of transport needs**

### *Selection and normalisation of proxies*

Data availability is often a determinant factor of model sophistication in the realm of transport modelling (Dimitriou, 2013). To balance such a trade-off, and avoid simplistic analysis resulting in unenforceable policies, this study proposes one proxy to each of the eight transport-related exclusion dimensions. In that sense, the proposed screening

framework is intended to cover at least partially all forms of exclusion emerging from transport issues that reinforce cycles of poverty.

This section of the paper aims to show that even in regions where transport-related data is very limited and very aggregated, the transport needs can still be proxied by open access indicators available at a municipality level. These proxy indicators are either directly selected from governmental databases (e.g. % of elderly or people with disabilities) or indirectly calculated from publicly available datasets. The following list briefly describes the rationale for the selection of the indicator that is applied to proxy each TRE dimension in Northeast Brazil. However, the same framework can still be replicated to other contexts using similar proxies that can capture the severity of each TRE dimension.

1. Physical: The demand for special transport facilities described by this dimension is measured by the share of the population of each municipality of over 65 years of age or with any disability (including mental, mobility, visual or hearing disabilities). For visual and hearing disability, only people with severe and total levels of impairment were taken into account. The dataset was retrieved from the latest Brazilian demographic census (IBGE, 2010).
2. Geographical: Since GTFS data is still very limited in the Global South (Pereira, 2019; Oloo, 2018; Evans et al, 2018) and informal mobilities are vital to billions living with poor road access (O'Brian and Evans, 2017), any attempt to measure the geographic exclusion dimension at a state or regional level built on the formal public transport network datasets would inevitably include too many areas with a coarse misrepresentation. Therefore, a simpler but rather consistent index is then applied to proxy this dimension. The Rural Accessibility Index (RAI) proposed by the World Bank studies (Roberts et al, 2006; Iimi et al, 2016) measures the share of people living farther than 2km from an all-season road.
3. From facilities: In a context where the facilities are not consistently mapped, and the majority of them are as a rule concentrated in the urban centres (IBGE, 2008; Church et al, 2000; Benevenuto & Caulfield, 2020).
4. Economic: To assess the severity of the economic needs preventing people from accessing desired destinations, this study applies a household per capita income indicator that measures the share of the population living with less than half of a minimum wage - which means R\$255.00 a month in the purchasing power parity of 2010. The individuals below this income line are considered to be at least vulnerable to poverty by the UNDP (2010).
5. Time-based: The only travel-time indicator consistently available for all the municipalities in the Brazilian census (IBGE, 2010) is the share of employed individuals who i) are vulnerable to poverty (same income strata mentioned above) and ii) spend more than two hours commuting every day.
6. Fear-based: The indicator utilised to proxy the fear-based dimension in the proposed framework is the ratio between the number of deaths per year per municipality caused by transport-related accidents (reported by the Brazilian Health Database – DATASUS, 2016) and the number of vehicles registered in each municipality (reported by the National Transit Authority - DENATRAN, 2016) multiplied by 100,000. The number of deaths considered in this study was an average of the latest years of data available (from 2009 to 2016).
7. Spatial: This dimension evaluates the exclusion caused by spatial barriers (e.g. gated communities, traffic intense roads, etc) that mostly affect low-income people who live in a walking world. To create a spatial indicator that measures

these barriers, an unpractical and currently non-existent amount of spatial data would be needed at a regional level. In that sense, alternatively, this study applies the concept of motorcycle ownership as a proxy for this dimension. It is argued that municipalities with high motorcycle ownership would be less vulnerable to exclusion caused by spatial barriers since low-income population would have higher access to low-cost motorised vehicles, either as their own private motorised transport or in the form of motorcycle taxis.

8. Social-position based: Since ethnicity-, race- and religion-based crimes in public space are as a rule not consistently measured across municipalities and over time, the selected proxy for this dimension had to be restricted to gender-based violence. Cases of verbal, physical and sexual violence against women perpetrated by strangers in public space (reported by the Brazilian Health Database - DATASUS, 2016) were considered into this dimension as an average of the latest years of available data (from 2009 to 2016). The ratio between the number of these cases and the female population multiplied by 10,000 is then taken as the final proxy for this transport-related exclusion dimension.

Since the selected indicators do not have comparable scales, normalisation and outlier removal are required before the hierarchisation process that is described in the next Section. The extreme outliers were identified and converted to the closest neighbour value in order to have a smoother range of values, while also keeping the shape of the original frequency distribution. After this, the normalisation of all the eight selected indicators was carried out leaving the data prepared for the pairwise comparison presented in next step.

#### *Weighting the transport-related exclusion dimensions*

Once the proxies were selected as described in the previous section, a weighting system is then proposed to evaluate the relevance of each dimension in comparison to the others within each municipality. This system is based on the Analytical Hierarchy Process established by Saaty (1980), which is still nowadays one of the most commonly used methods for multi-criteria decision analysis in transport projects (Macharis and Bernardini, 2015; Jones et al., 2013; Thomopoulos et al., 2009). For the purpose of this study, the Analytic Hierarchy Process (AHP) has only been applied to calculate the weights (also called the eigenvector) of the TRE dimensions. The following flow chart presents the steps taken based on the AHP method to estimate the relative importance (i.e. weights).

An important aspect of research is that while traditional weight calculations using AHP rely on surveys or personal opinion judgment at the pair-wise comparison step, the approach that is proposed applies objective judgment rules based on numerical comparison of indicators. Therefore, the weights derived from this process are less susceptible to manipulation or strong interference of private agendas of decision-makers.

The judgment rules applied to the pairwise comparisons of the normalised proxy indicators are presented in Table 2. In summary, when two given dimensions are compared by their normalised proxies, the higher is the first proxy is in comparison to the second, the higher is the score assigned to this pairwise comparison. For instance, if the normalised proxy indicators for the “time-based” and the “fear-based” exclusion dimensions are 0.60 and 0.20 respectively, the pairwise comparison following the

judgment rules proposed in Table 2 result in a score of 9 (since the first dimension (i.e.  $D_i$ ) is more than 100% greater than the second dimension (i.e.  $D_j$ )). Scores like this one are then used to populate the AHP matrix (exemplified by Tables 2 and 3) in which the final dimensions' weights are finally calculated. Since the indicators are compared only after the normalisation and outlier removal, differences of over 100% between a pair of indicators would represent a significant variation in absolute terms. Therefore, the maximum and minimum scores (i.e. 9 and 1/9) are given to variations of over 100% between the dimensions. The other seven intermediate scores are defined considering an even distribution of variation among these intermediate bands, as shown in Table 2 below.

**Table 2: Judgment rules applied to each pair of transport-related exclusion dimensions**

| Pairwise comparison                                   | Score |
|-------------------------------------------------------|-------|
| $D_i$ is more than 100% greater than $D_j$            | 9     |
| $D_i$ is between 75% and 100% greater than $D_j$      | 7     |
| $D_i$ is between 50% and 75% greater than $D_j$       | 5     |
| $D_i$ is between 25% and 50% greater than $D_j$       | 3     |
| $D_i$ is between 25% lower and 25% greater than $D_j$ | 1     |
| $D_i$ is between 50% and 25% less than $D_j$          | 1/3   |
| $D_i$ is between 75% and 50% less than $D_j$          | 1/5   |
| $D_i$ is between 100% and 75% less than $D_j$         | 1/7   |
| $D_i$ is more than 100% lower than $D_j$              | 1/9   |

The matrices displayed in Tables 3 and 4 show samples of the pairwise comparison of dimensions done by the AHP method. These are two cases out of the 1,990 municipalities analysed by the same framework. The weights shown at the last column of this matrix have been computed by the technique proposed by Kostlan (1991). This approximation method was selected since it is one of the most commonly used techniques that simplify the original calculation process proposed by Saaty (1980), reducing dramatically the computational power needed to solve 1,900 matrices simultaneously, while also keeping only less than 10% of variation from the exact eigenvector (Vargas, 2010).

**Table 3: Matrix showing a sample of the computed weights - Ipupiara, Bahia state**

| Dimension s     | From facilities | Economic | Spatial | Geographic | Time-based | Physical | Fear-based | Social position-based | Weights |
|-----------------|-----------------|----------|---------|------------|------------|----------|------------|-----------------------|---------|
| From facilities | 1               | 7        | 9       | 9          | 9          | 5        | 9          | 9                     | 39%     |
| Economic        | 1/7             | 1        | 1       | 9          | 9          | 1/3      | 9          | 9                     | 13%     |
| Spatial         | 1/9             | 1        | 1       | 9          | 7          | 1/5      | 9          | 9                     | 12%     |
| Geographic      | 1/9             | 1/9      | 1/9     | 1          | 1/9        | 1/9      | 1/9        | 9                     | 3%      |
| Time-based      | 1/9             | 1/9      | 1/7     | 9          | 1          | 1/9      | 9          | 9                     | 8%      |
| Physical        | 1/5             | 3        | 5       | 9          | 9          | 1        | 9          | 9                     | 19%     |
| Fear-based      | 1/9             | 1/9      | 1/9     | 9          | 1/9        | 1/9      | 1          | 9                     | 5%      |

|                       |     |     |     |     |     |     |     |   |    |
|-----------------------|-----|-----|-----|-----|-----|-----|-----|---|----|
| Social position-based | 1/9 | 1/9 | 1/9 | 1/9 | 1/9 | 1/9 | 1/9 | 1 | 1% |
|-----------------------|-----|-----|-----|-----|-----|-----|-----|---|----|

**Table 4: Matrix showing a sample of the computed weights – Bom Jesus das Selvas, Piauí state**

| Dimensions            | From facilities | Economic | Spatial | Geographic | Time-based | Physical | Fear-based | Social position-based | Weights |
|-----------------------|-----------------|----------|---------|------------|------------|----------|------------|-----------------------|---------|
| From facilities       | 1               | 3        | 1       | 3          | 3          | 9        | 3          | 9                     | 29%     |
| Economic              | 1/3             | 1        | 1       | 1          | 1          | 9        | 1          | 7                     | 14%     |
| Spatial               | 1               | 1        | 1       | 1          | 1          | 9        | 1          | 7                     | 16%     |
| Geographic            | 1/3             | 1        | 1       | 1          | 1          | 9        | 1          | 5                     | 13%     |
| Time-based            | 1/3             | 1        | 1       | 1          | 1          | 1/5      | 7          | 1                     | 12%     |
| Physical              | 1/9             | 1/9      | 1/9     | 1/9        | 5          | 1        | 5          | 1/9                   | 2%      |
| Fear-based            | 1/3             | 1        | 1       | 1          | 1/7        | 1/5      | 1          | 1                     | 12%     |
| Social position-based | 1/9             | 1/7      | 1/5     | 1/5        | 1          | 9        | 1          | 1                     | 2%      |

After calculating the dimensions' weights, a consistency test was then performed following **Error! Reference source not found.** to evaluate whether the weights are appropriately reflecting the relative judgments (for example, if  $D_1 > D_2$  and  $D_2 > D_3$  it would not be consistent to have  $D_1 < D_3$ ). This test is particularly important to check for consistency in cases where two or more dimensions present very low values (close to zero). Since the judgment rules are computed based on the result of a division of two dimensions, close-to-zero values in the denominator can compromise the pairwise comparisons. Therefore, the consistency test is applied following see Equation 1 as proposed by Saaty and Vargas (2006). If the ratio between the Consistency Index ( $CI$ ), and the Random Consistency Index ( $RI$ ) is below 10%, the weights are considered to be consistent (Saaty and Vargas, 2006). This ratio is also called as the Consistency Ratio ( $CR$ ). Therefore, if  $CR < 10\%$  the calculated weights are accepted.

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

Where:

$CI$  is the consistency index  
 $\lambda_{max}$  is the maximum eigenvalue  
 $n$  is the number of dimensions

**Equation 1**

#### *Prioritisation scores calculation*

Finally, a prioritisation score is proposed taking the weights and the normalised proxies as inputs. This step is crucial to combine the priorities at a local and regional level into the same indicator. While the normalised proxies ( $Np_{ij}$ ) indicate the severity of a TRE dimension in a given municipality in comparison to the region (regional priority), the weights ( $w_{ij}$ ) shows the respective severity of this dimension when compared to the other dimensions of the same municipality (local priority). Hence, the prioritisation score ( $PS_{ij}$ ) at a municipality level is proposed by Equation 2, combining these two factors - how important a given dimension is at a local level, and how severe the same dimension is in a municipality comparing with the regional figures.

$$PS_{ij} = w_{ij} * Np_{ij}$$

Where:

- $PS_{ij}$  is the priority score of the dimension  $i$  in municipality  $j$
- $w_{ij}$  is the weight of the dimension  $i$  in municipality  $j$
- $Np_{ij}$  is the normalised proxy of the dimension  $i$  in municipality  $j$

### Equation 2

#### *Cluster analysis and evaluation of priority regions*

Whilst the priority indicators proposed can be applied for example to funding prioritisation of local transport investments (at the municipality level), a final step is still needed to identify where interventions at a regional level are most needed. Thus, a spatial cluster analysis is proposed for each of the eight transport-related exclusion dimensions measured by the prioritisation scores. By doing so, it becomes possible to spot patterns of transport-related exclusions at a regional level, showing priority areas where a given dimension is severe in both, absolute ( $Np_{ij}$ ) and relative ( $w_{ij}$ ) terms. The outputs of this analysis offer an objective answer at a regional level to the third research question, providing evidence-based guidance for transport policies aiming at poverty reduction. In summary this is possible by i) defining regions (clusters of municipalities) sharing a higher need for specific transport interventions, ii) evaluating the level of governance at which these interventions are needed, and iii) identifying top-priority areas that accrue more overlapping clusters of transport-related exclusion dimensions.

Firstly, an incremental analysis was performed to check for global spatial autocorrelation of the prioritisation score at different distance bands. This analysis is an essential step to identify the size in which the clusters reach maximum spatial autocorrelation. That is, the number of neighbour municipalities that results in fewer chances of a given transport-related exclusion dimension being randomly distributed across the entire region. As this study has been developed using the ArcGIS platform, the recommended method for this in the literature is the Moran's I test of global spatial autocorrelation (Mitchell, 2005).

In this analysis, the z-scores are plotted versus a series of increasing distances varying from 5 km up to 1,200 km in some cases. According to Mitchell (2005), z-scores reflect the intensity of spatial clustering (or randomness). Therefore, statistically significant peaks of z-scores are considered to be appropriate distance bands (distance radius parameters) for measuring also spatial clusters (hot spots). In other words, the distance bands that represent the maximal clustering pattern of each Priority Score can then serve as inputs to the final evaluation of regional hotspots that will show the areas that should be prioritised in future transport interventions for each TRE dimension.

Thus, after identifying the distance bands of each TRE dimension, a local cluster analysis could be then performed using the technique proposed by Getis and Ord (1992) by means of ArcGIS. In a more recent study, Getis and Ord (2010) argue that when Moran's I tests are used in conjunction with their Gi\*-statistics methods (Ord and Getis, 1995), local "pockets" of dependence may be identified giving rise to spatial associations. Finally, the location of these pockets of priority scores that proxy

transport-related exclusion dimensions are suggested to be priority areas that are in most need for specific transport interventions at a municipal and regional level.

## **Results and Discussion**

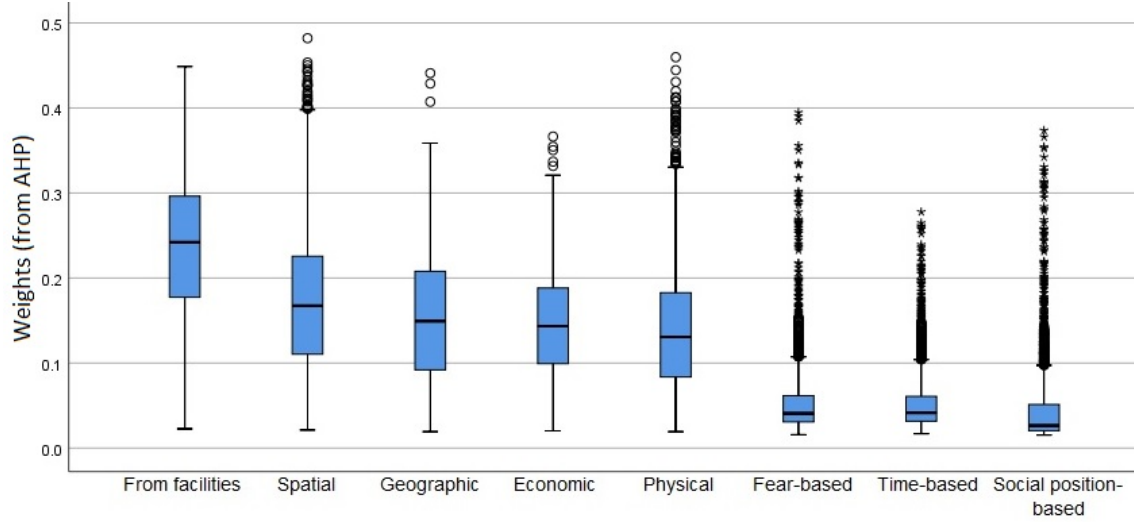
### *Weighting factors*

The first test performed after calculating the weights of each dimension was the consistency test described by Equation 1. The maximum consistency ratio found among all the 1,990 cases was less than 6%. As this value is below the consistency ratio limit (10%), all the calculated weights can, therefore, be considered consistent. In other words, all the generated weights reflect appropriately the relative scale of priorities determined by the comparison judgments rules (presented in Table on page 7).

The boxplots in Figure 2 describe statistically the weights of the transport-related exclusion dimensions obtained by the AHP matrices of the 1,990 municipalities included in this case study. Based on the averages presented on this graph, it is possible to observe that exclusion from facilities stands out as the highest priority in the region overall. This fact demonstrates that the most recurrent transport issue in Northeast Brazil is related to the lack of access to basic services and opportunities.

In addition, Figure 2 also points out to other two groups of dimensions with an overall second and third level of importance among the municipalities of this region. The first group is composed of the Spatial, Geographic, Economic and Physical dimensions. This group presents similar levels of relative priority, showing that, as a rule, there are only minor variations of the weights of these dimensions among the municipalities.

As can also be noted in Figure 2, the third level of relative priority is composed of the fear-based, time-based and social position-based dimensions. Since the distribution of the proxies of these dimensions is highly skewed (not normally distributed), a substantial number of outliers are displayed when evaluating their overall average. This fact denotes that, while most of municipalities are not much affected by these three transport-related exclusion dimensions, in a few specific municipalities (outliers) these dimensions do represent critical transport issues that require high priority. The variations of these indicators throughout the municipalities contrast particularly with the Geographic and From Facilities dimensions, which present a much more parametric distribution (i.e. less skewed and with fewer outliers). It is worth noting that these two dimensions are related to the level of remoteness (from all-season-roads and town centres) in which the inhabitants of each municipality live. This fact highlights once again that the spatial burden separating people from opportunities in Northeast Brazil is a key priority to be addressed even when compared to the other TRE dimensions.



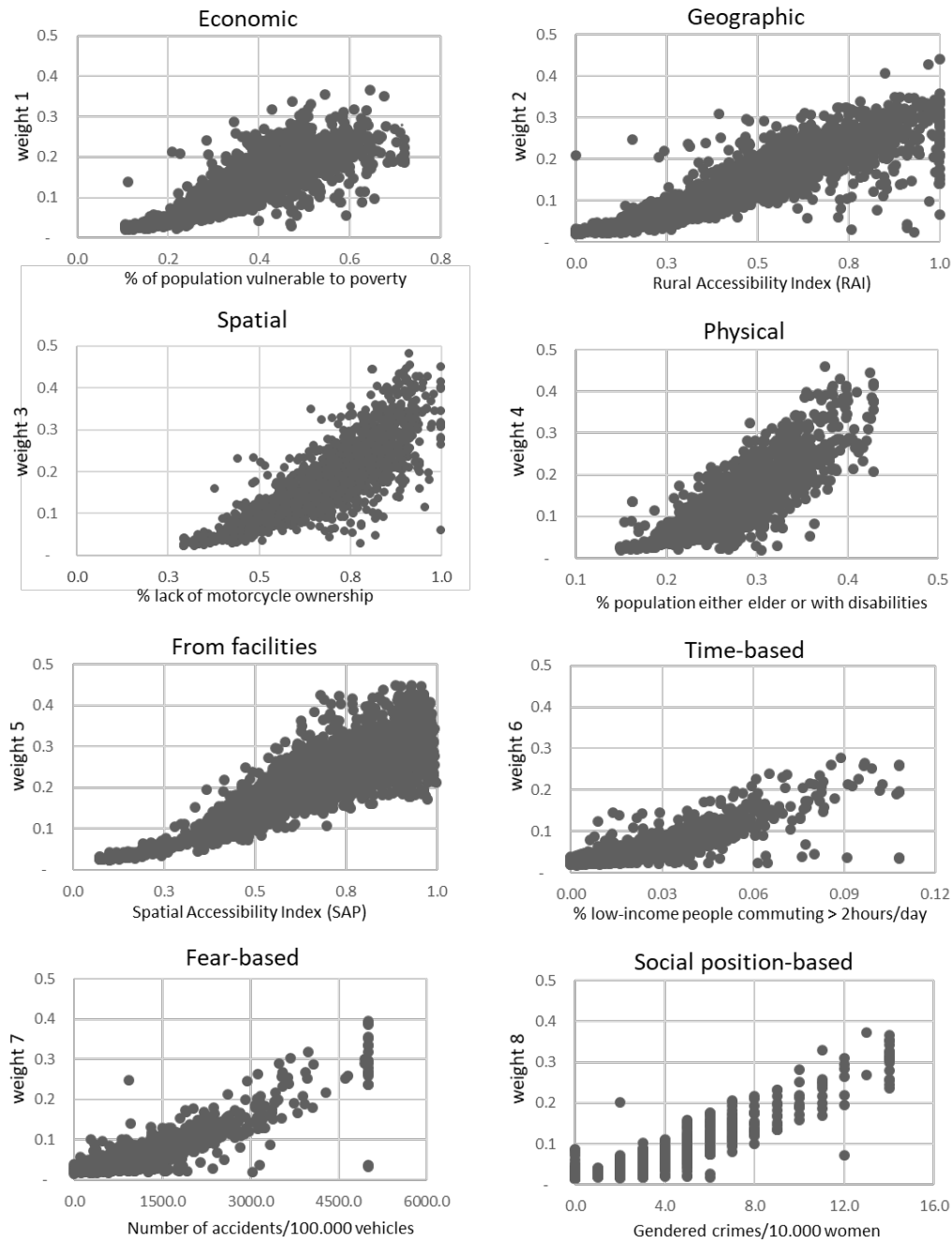
**Figure 2: Distribution of weights estimated by AHP to each transport-related exclusion dimension**

As can be expected, by following the objective judgment rules proposed in Table 2, the average weights and their frequency distribution tend to follow the same patterns of the original indicators (proxies) on which they are base. Therefore, it is worth mentioning that, even after the normalisation and the outlier removal, it is likely that the indicators with a negatively skewed frequency distribution would tend to have higher weights on the overall average. That is, the higher the normalized average of a proxy indicator, the higher its respective average weight.

Nevertheless, the skewness of the overall input data, in this case, should not be taken as a caveat in the model since it also represents the regional trends in terms of transport needs. Moreover, the distribution of the overall data does not affect the hierarchisation process at a local level since it is done considering only the relative importance of the local indicators.

Figure 3 shows that, despite having a clear relationship between the proxy indicator and its respective weight, a substantial variability can be also observed in the dispersion graphs. This fact reveals the relevance of the hierarchisation model. By assessing the relative importance of specific transport-related exclusion dimensions in comparison to the others, it is possible to understand the nature of transport interventions that are primarily needed. In a context with several transport needs and limited budget, these results may help guide the prioritisation of transport investments to tackle poverty more effectively.

Finally, this variability also shows that the same value of a proxy indicator may represent different priority levels depending on the municipality. However, as they have different local weights, the final priority score ( $PS_{ij}$ ) obtained for the same dimension (from facilities) is 2.35 times higher for the latter municipality when compared to the former. This example emphasises the importance of having an evidence-based comparison of the local needs when establishing priority areas and priority lines of action for transport interventions.



**Figure 3: Distribution of weights derived from AHP by each indicator**

#### *Incremental spatial autocorrelation*

The results obtained from the incremental spatial autocorrelation (ISA) analysis are summarised in Figure 4. Except for the first iteration ( $D = 5$  km) of all the eight graphs, the following reported results are all statistically significant at a 99% confidence level (i.e.  $p\text{-values} < 0.01$ ). This exception is due to the various sizes of the municipalities being sometimes too large to have a neighbour within the first 5 km of radius from its centre point. Nonetheless, as all the peak points of the eight graphs of Figure 4 (represented by the red dots) are far greater than 5 km, no further impacts are expected to be introduced in the incremental analysis by having the first iteration not statistically significant.

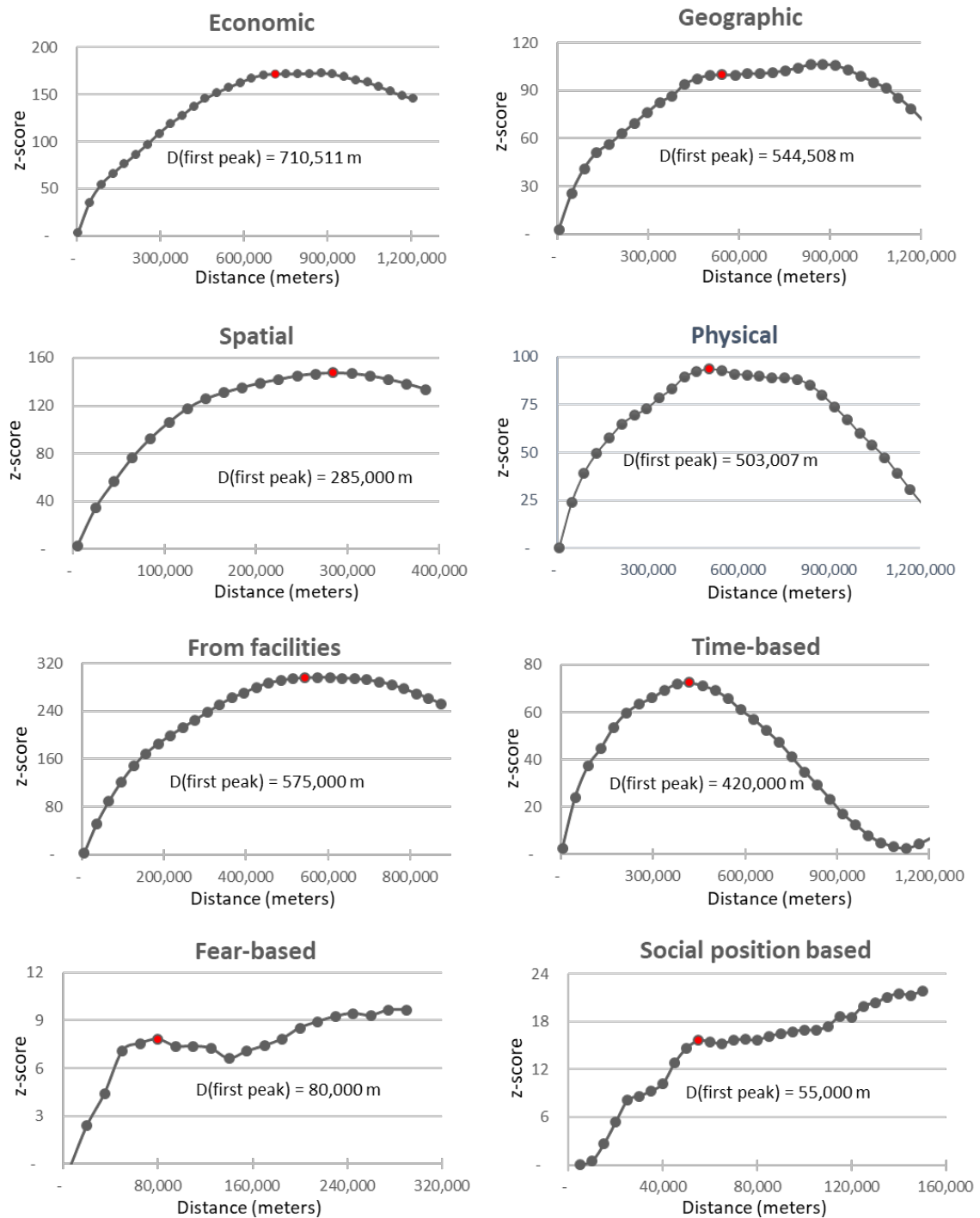
According to Mitchell (2005), the null hypothesis evaluated by Moran's I test is that the spatial data being analysed is randomly distributed among the study area. In that sense, if the p-value is statistically significant and the z-score is positive, the null hypothesis can be rejected, meaning that the spatial distribution of high and/or low values is probably too unusual to be a result of a random chance. Thus, since the results show z-scores greater than 2.58 (critical value according to Mitchell, 2005) and p-values lower than 0.01, it can be inferred that there is a clustering pattern in the spatial distribution of this data. In the context of this analysis, a statistically significant cluster points out to municipalities that are affected by the same transport-related exclusion dimension and, thus, can be targeted at a local and regional level with similar transport interventions.

Figure 4 shows that the intensity of the z-scores can reach one or more peaks as the incremental distance increases. These peaks indicate distances where spatial clustering is most pronounced (Mitchel, 2005). As already explained in Section 6.3.3, these peaks (often the first one) are appropriate values to use for tools with a distance band (e.g. Getis-Ord Gi\* local cluster analysis, which are further discussed in Section 6.4.3). For cases such as the Geographic, Fear-based and Social position-based dimensions, where two peaks have been found by the ISA analysis, only the first peak was then considered as the chosen distance band. In other words, for these three cases in which two significant distance bands were revealed by the ISA analysis, only the smallest one was taken into consideration for further hotspot analysis.

Moreover, the incremental analysis in Figure 4 demonstrates that spatial clusters formed by the prioritisation scores of the social-position, fear, and time-based dimensions are smaller than the other six dimensions ( $D(\text{first peak}) < 100,000 \text{ m}$ ). With regards to the spatial dimension ( $D(\text{first peak}) = 285,000 \text{ m}$ ), even though it refers to physical barriers of the local built environment, it is possible to conclude that a slightly wider group of neighbour municipalities also appear to share the same spatially excluding issues. Given this relatively low distance bands, these findings suggest that transport issues related to social exclusion based on these four dimensions tend to be much more concentrated than a regionally rooted problem in the evaluated area.

On the other hand, the dimensions related to physical, geographic, from facilities, and economic issues have their maximum intensity of spatial clustering at a wider range ( $D(\text{first peak}) > 500,000 \text{ m}$ ). This fact suggests the transport interventions aiming at these dimensions, beyond targeting specific high ranked municipalities within the clusters, should also devise strategies to cope with these issues at a sub-regional or even state-wide level.

In summary, these results point out the scale of interventions that are needed for each of the transport-related exclusion dimensions in the case study region. The evidence has shown that while some dimensions are much more localised (e.g. social position and fear-based), others require transport interventions at a regional scale (e.g. geographic, economic, and physical). Further results are provided in the next Section showing where these interventions are mostly needed by providing the location of the hotspots of each dimension. This results finally emphasises how transport development can tackle multi-dimensional poverty in these regions.



**Figure 4: Incremental global spatial autocorrelation analysis (Moran's I) of the prioritisation scores of the transport-related exclusion proxies**

#### *Local spatial cluster analysis*

The first z-score peak of each dimension, resulting from the incremental autocorrelation analysis, was then used as an input for the local spatial pattern association analysis, also referred as hot spot analysis (Ord and Getis, 1995). Figure 5 presents the maps that

emerged from such an analysis. These results depict clusters of high positive z-scores (hot spots) as well as those with an intense negative z-score (cold spot). The level of confidence is also disaggregated into four confidence intervals (99%, 95%, 90% and not significant).

For a given dimension, an area considered to be a statistically significant hot spot (red) indicates that the municipalities within this area have high prioritising scores ( $PS_{ij}$ ) surrounded by other municipalities with high values as well (Mitchel, 2005). In other words, the statistically significant hot spots depicted in Figure 5 point to areas where the municipalities are severely affected by a given transport-related exclusion dimension both from a local and regional point of view (see Equation 2). In this way, these maps offer supporting evidence for tailored specific interventions that can better address poverty through transport policies and investments.

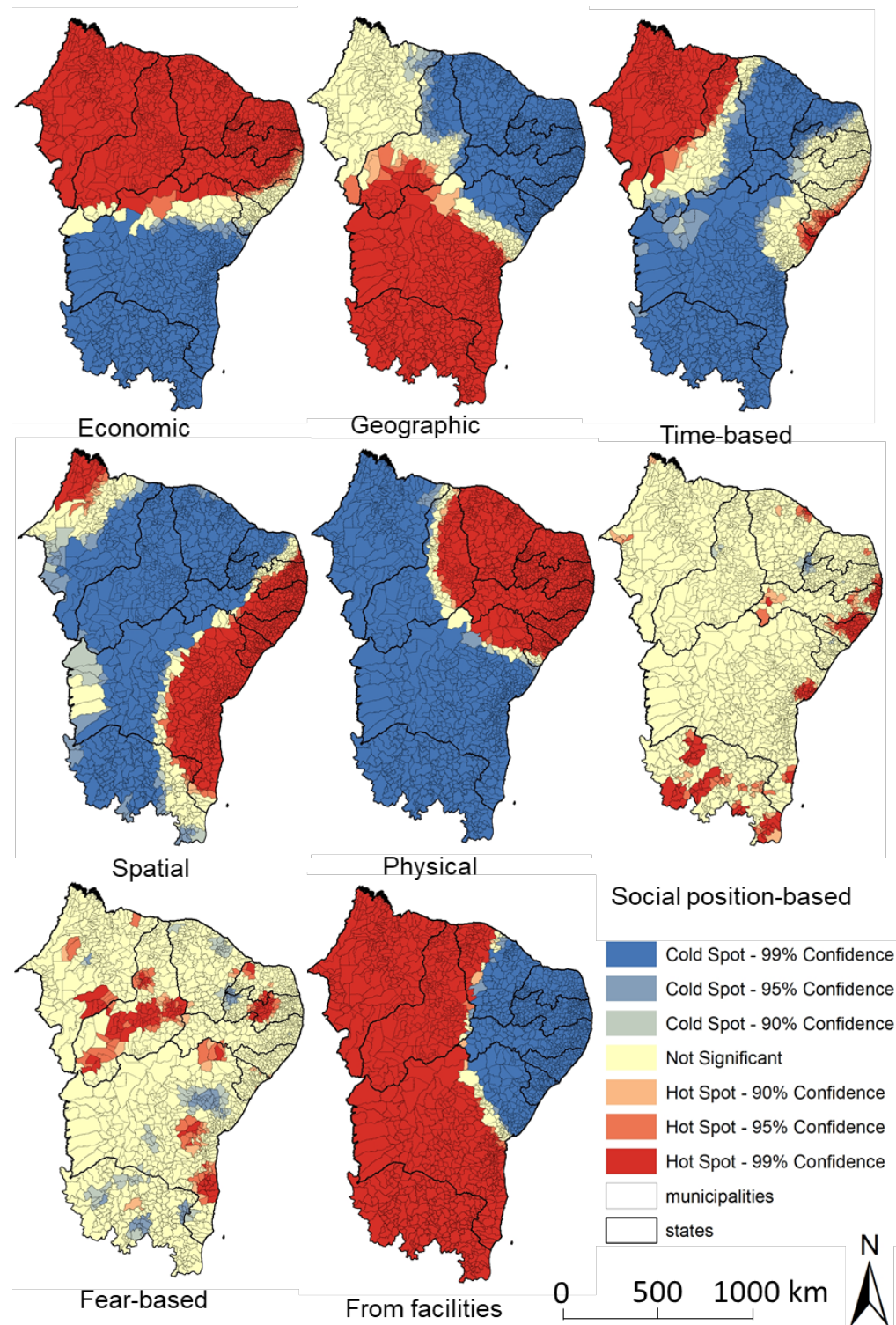
Church et al (2000) highlight marginal improvements to physical accessibility in areas which already have high standards of this dimension may result in little difference to residents whose main barrier to movement is due to time-based or cost constraints. Applying this concept to the example of Ipuíara (shown at Table 3), the construction of new rural roads (i.e. *geographic* dimension which weight is 3%) is not expected to be as effective in reducing poverty as improvements in access to schools or healthcare (i.e. *from facilities* dimension, which weight is 39%), for example.

In response to this, the identification of these hot spots presents a crucial tool capable of identifying the priority areas in need of specific transport interventions, as well as the most pressing transport issue that is likely to be reinforcing the poverty trap in these areas. In fact, as can be seen in the maps of Figure 5, these eight dimensions are very often intertwined, and the same area falls within more than one hot spot, especially in areas under severe circumstances of deprivation. Nevertheless, by separating out these maps it is possible not only to evaluate the interactions of these transport-related exclusion dimensions but also to draw regional strategies for a socially driven transport planning.

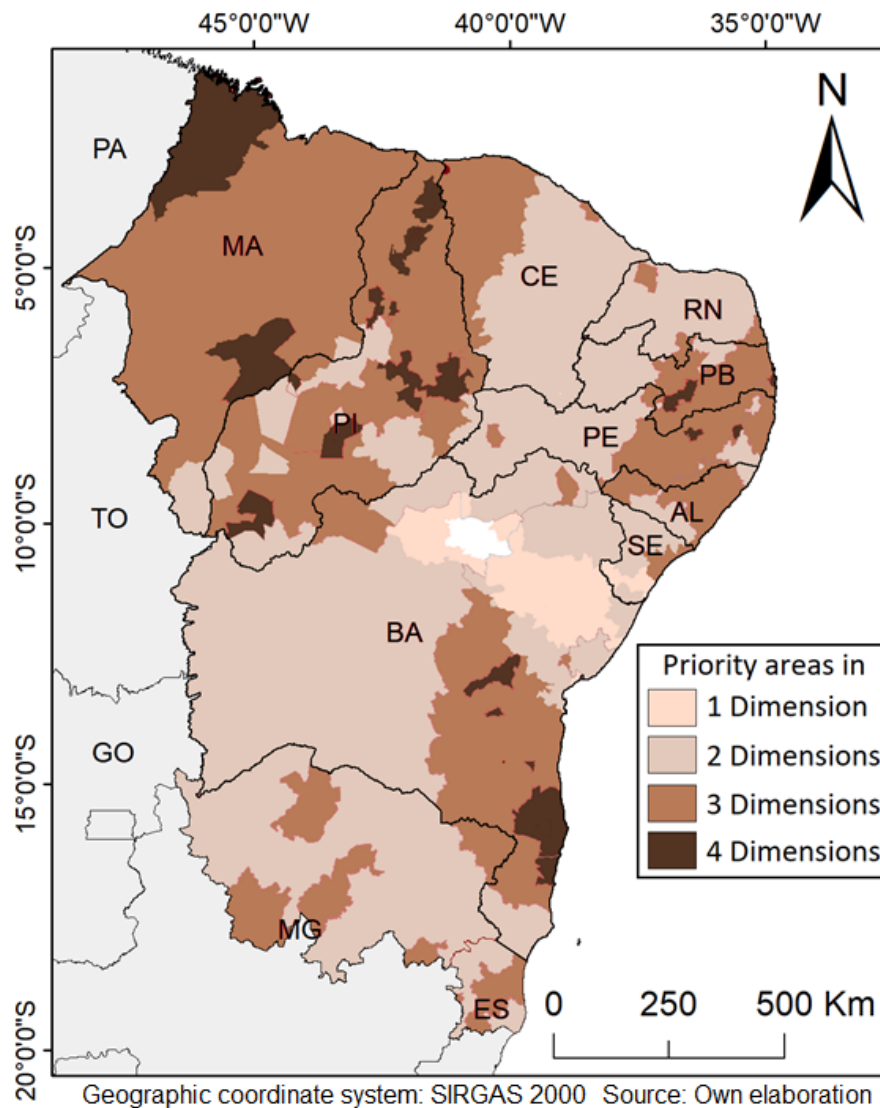
Finally, Figure 6 combines all the statistically significant hot spots at 99% confidence into the same map. This map depicts regions where there is overlapping of four transport-exclusion dimensions, bringing particular attention to the states of Maranhão (MA) and Piauí (PI), which are vastly covered by priority areas of 3 and 4 dimensions. Minor, yet still significant, spots of fourfold overlapping can be also spotted in Southeast of Bahia (BA), centre of Paraíba (PB) and Pernambuco (PE).

It can thus be concluded that, since these areas are affected by severe levels of multidimensional transport-related exclusion, that they might require higher priority than the others. Particularly the state of Maranhão (MA), which is entirely immersed in issues related to income poverty (*economic*), long commuting times (*time-based*), and low access to opportunities (*from facilities*), is an obvious concern clearly in need of urgent socially driven transport interventions. Taken together, these results suggest that transport planning in Northeast Brazil can and should be sensitive to social issues by including quantitative analysis, as is proposed in this study, into screening frameworks and appraisals of transport projects.

Overall, these findings elucidate a crucial step in the process of planning transport for poverty alleviation. By knowing the nature of the most critical transportation needs and the areas where they are most severe, targeted transport initiatives can be more effectively planned to break the factors that perpetuate the poverty cycle.



**Figure 5: Local spatial cluster (Getis-Ord Gi\*) analysis of the prioritisation scores of the eight transport-related exclusion dimensions applied to Northeast Brazil**



**Figure 6: Priority areas at 99% of confidence based on the transport-related exclusion screening framework applied to Northeast Brazil**

## Conclusions

The framework proposed in this case study has sought to offer a screening framework that can support transport planning in Northeast Brazil by identifying transport issues that are likely to be reinforcing poverty traps both at the municipality and regional level. By applying publicly available data to well-established MCDA and spatial cluster analysis, the proposed methodology has been able to identify priority areas and priority lines of action to tackle poverty more effectively through transport development.

Previous research has documented the lack of tools for appraising social issues in transport planning (Geurs et al 2009; Van Wee and Geurs, 2011; Jones and Lucas, 2012). On the other hand, the links between transport development, social exclusion, and poverty have been increasingly recognised in the literature (Church et al 2000; Lucas, 2012). In that sense, this research contributes to the literature by proposing a

framework capable of performing a transparent and objective analysis of the social dimension that can complement mainstream transport planning techniques. This framework is particularly tailored to the context of Northeast Brazil, where the poverty level is most severe in the Country and where the social dimension of transport has been continuously neglected at the planning stage.

Transport and accessibility are directly related to the structures, processes and livelihood strategies that affect the inter-generational transfer of poverty. The findings reported throughout this study reflect an effort to clarify which transport-related exclusion dimension should be mainly targeted at in each municipality and sub-regions in order to break the cycles of poverty.

The results have shown that municipalities within the Northeast region present different transport needs and suffer from a range of transport externalities. Therefore, the methodology of screening priorities at a sub-regional level (by clusters) and at a local level (by priority scores) can provide a systematic and evidence-based social analysis to guide transport policies.

Furthermore, the findings also highlight that whilst some areas are particularly affected by a single dimension (e.g. west of Bahia and east of Ceará states), others are overlapped by four dimensions (e.g. North of Maranhão and Center of Pernambuco states). This fact sheds light on specific sub-regions and municipalities that deserve higher priority and targeted transport interventions. Overall, it is also worth mentioning that only two out of 1990 municipalities of the entire case study region were not found in any statistically significant hot spot (considering 99% confidence). Revealing, thus, the relevance and the need for socially driven transport interventions in Northeast Brazil.

Future research is needed to integrate the weights generated by the presented framework into MCDA-based social appraisals of potential transport projects. Likewise, more detailed and comprehensive proxies should be further explored in future as soon as disaggregated poverty- and transport-related data becomes available for these municipalities. Nonetheless, for any region or municipality where this data is already available, this methodology can still be adapted to harness more transport-related exclusion indicators through this screening framework and reorient transport planning towards more effective poverty reduction strategies.

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