

# **Countering Urban Segregation in Brazilian Cities: Policy-oriented Explorations Using Agent-based Simulation**

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## **Countering Urban Segregation in Brazilian Cities: Policy-oriented Explorations Using Agent-based Simulation**

**Abstract.** This paper uses agent-based simulations to explore the impact of social-mix policies on the segregation dynamics of São José dos Campos, a medium-sized Brazilian city. It uses the model MASUS, Multi-Agent Simulator for Urban Segregation, to test two policy strategies: one based on the spatial dispersal of poverty, and the other on the spatial dispersal of wealth. The experiments indicated that these strategies reveal varying shortcomings and complementary benefits in cities like São José dos Campos. While poverty dispersal provides immediate results on segregation levels and direct benefits for the assisted families, wealth dispersal can produce long-term outcomes and promote a positive change in the overall levels and patterns of segregation in the city.

**Keywords.** urban segregation, social mix, urban policies, social simulation, agent-based model, Brazil.

### **1 Introduction**

Despite being the largest economy in Latin America, Brazil remains among the nations with the highest indicators of income inequality in the world (PNUD, 2010). Such inequality has implications for the spatial organization of cities, where *income segregation* represents one of their most outstanding features, with impacts that reinforce the social exclusion of disadvantaged families (UN-Habitat, 2010). In Brazil and other Latin American countries, the dynamic relationship between income segregation and social exclusion has often created a continuous downward spiral: segregation promoting exclusion, and exclusion promoting segregation. On the one hand, the legal market for affordable and habitable

housing in these countries has proven incapable of meeting the needs of socially excluded families. For these families, informal and clandestine means of accessing and occupying urban land are often the only available alternative. Such exclusionary reality promotes the consolidation of highly segregated settlements, characterized by deprivation and non-realization of housing rights (UN-Habitat, 2010). On the other hand, segregation imposes difficulties on the daily life of disadvantaged families that perpetuate or worsen their condition of exclusion. For example, poor segregated areas have been consistently associated with higher exposure to violence and diseases, prejudice and territorial stigmatization, decreased accessibility that imposes time-consuming trips to work or school, and low quality of the built and natural environment (Sabatini *et al.*, 2001).

While housing policies in many developed countries have long focused on minimizing segregation and its negative effects (Allen *et al.*, 2005; Galster, 2007), Brazil still presents a wide disparity between the scientific debates that advocate spatial integration of social groups and the actual policy practice. For example, Brazilian housing policies remain relying on strategies that have been condemned and avoided in other countries, like the creation of large social housing settlements for the poor that are located on cheap land in the outskirts of the city. By focusing exclusively on minimizing the housing deficit, this type of policy displaces poor families to isolated areas, distant from the supply of equipment, services and opportunities, which very often turn into distressed neighbourhoods (Rolnik, 1997; Sabatini, 2006).

Designing and implementing policies that effectively promote integration among different social groups is not an easy task. Studies evaluating the experience of developed countries present several divergences concerning the impact of social mix policies (Feins and Shroder, 2005; Smets and den Uyl, 2008) and indicate that there is no single formula for

success. Expected achievements are not likely to be attained without well-informed policies that address the local particularities of mechanisms that influence segregation dynamics.

Studies that improve our understanding about the dynamics of segregation are essential for the development of social-mix policies. Nevertheless, such studies are challenged by the fact that segregation presents features commonly associated with *complex systems*, which, according to Batty and Torrens (2005:754), are entities that are “coherent in some recognizable way but whose elements, interactions, and dynamics generate structures and admit surprise and novelty that cannot be defined a priori”. From this perspective, segregation can be seen as an emergent structure or property of a complex urban system. Its consistent patterns, observable at the macro level, emerge from interactions between many families at the micro level, who are constantly making decisions about their residential location.

The complex nature of segregation is better represented by tools that are capable of capturing its dynamics from the bottom-up, prioritizing the process rather than the product (Batty *et al.*, 2006). Considering that, this paper adopts an agent-based modeling (ABM) approach, based on individual decision-making units, called agents, which interact with each other and their environment (Gilbert, 2008). By explicitly simulating interaction processes that occur at a micro-level, ABM enables researchers to explore the emergence of macro structures from bottom-up in a very natural way (Miller and Page, 2007).

This paper uses agent-based simulations to explore the impact of social-mix policy approaches on the segregation dynamics of a Brazilian city. The simulations were performed with MASUS (Multi-Agent Simulator for Urban Segregation), an empirically-based model that provides a laboratory for studying the emergence of segregation patterns. The model MASUS was proposed and extensively described by Feitosa *et al.* (2011). In the present paper, MASUS is used to test and compare the outcomes of two different social-mix policy

strategies: one based on the spatial dispersion of poverty, and the other on the spatial dispersion of wealth. The first promotes integration by moving poor households out of problematic neighbourhoods, whereas the second stimulates the construction of residential developments for middle and upper classes in poor regions of the city. The experiments relied on empirical data collected at São José dos Campos, a medium-sized city in the State of São Paulo, Brazil.

## **2 Promoting and countering urban segregation**

Identifying mechanisms that influence the emergence of segregation is an important step towards the development of effective social-mix policies. Considering existing studies, it is possible to identify approaches focusing on the following mechanisms: personal preferences, labour market, land and real estate markets, and the state. The first approach, which concentrates on *personal preferences*, offers a limited contribution for the development of social-mix policies, since it analyses segregation as a social practice that results from the attempt of some families to reinforce their social identities through shared values and to improve their quality of life.

The second approach considers the inequalities of the *labour market* and its socio-economic impacts as being responsible for segregation and the precarious life conditions of part of the urban population (Lago, 2000). To counteract segregation, this approach calls for structural macroeconomic policies, such as fiscal and monetary policies, as well as long-term investments in public education and health care.

The third approach focuses on the dynamics of *land and real estate markets*. It stresses how real estate agents stimulate a competition for housing that reinforces the self-segregation of higher income groups and the exclusion of disadvantaged families (Abramo, 2001). The state can play an active role in mitigating segregation impacts related to the land

and real estate market by setting initiatives to regulate its dynamics, like creating measures to diversify land use and promoting developments for upper classes in areas occupied by disadvantaged families. This stimulus to promote the *spatial dispersion of wealthy families* can occur through public investments in infrastructure and security, changes in the norms of land use, tax exemption measures, and concessions (Sabatini, 2006).

While the previous discussion demonstrates the importance of governmental institutions in regulating mechanisms that promote segregation, some studies focus on how the *state* can also intensify segregation through its permissiveness, urban legislations, or investments (Rolnik, 1997). Examples include the widespread practice of exclusionary zoning, the unequal distribution of urban investments, and social housing projects that result in large areas of poverty concentration. In the United States and some European countries, where minimizing urban segregation became a target explicitly expressed in policy debates, many of these practices were already recognized as a mistake and several social-mix strategies have been adopted to integrate different social groups.

Policy strategies for promoting integration through the *spatial dispersion of poverty* focus on moving low-income households out of distressed areas into wealthier neighbourhoods. Examples of housing programs that adopt this strategy include the Moving to Opportunity and HOPE VI (Housing Opportunities for People Everywhere) in the United States, which distribute housing vouchers to low-income families for use when renting private dwellings in neighbourhoods with low poverty rates.

The *renewal of troubled neighbourhoods*, a strategy that has also been adopted in some developing countries, includes measures to improve local services and social programs, oppose delinquencies and territorial stigmas, demolish high-density construction, build high-quality houses, and encourage middle-class households to move into these areas. Another social-mix strategy involves *regulating new developments* by requiring mixed occupancy as a

condition for approval or funding. These regulations often allow local authorities to negotiate a percentage of affordable units within new residential developments in exchange for planning permission (e.g., Section 106 of the UK's Town and Country Planning Act 1990).

There are many divergences regarding the impact of policies aimed at minimizing segregation. Some studies identify several accomplishments and judge many policies to be successful (Feins and Shroder, 2005), while others focus on their failure and the need for restructuring them (Smets and den Uyl, 2008). Such divergences reinforce the relevance of constantly monitoring and adjusting policies to attain the expected results. Most importantly, the design of these policies must consider the particularities of cities, which differ in segregation patterns, population composition, levels of deprivation, culture, structure of housing markets, and many other features that demand specific approaches.

### **3 The MASUS model**

This work uses the model MASUS (Multi-Agent Simulator for Urban Segregation) to assess the impact of different social-mix policy approaches in a Brazilian context. This section provides a brief introduction to MASUS, while its detailed description and theoretical specifications can be found in Feitosa *et al.* (2011).

MASUS is a scientific tool designed to represent segregation as an emergent property of complex urban systems and to serve as a laboratory that provides alternative scenarios that:

- Explore the impact of different contextual mechanisms on the emergence of segregation patterns
- Support planning actions by offering insights about the adequacy of policy strategies.

Since MASUS relies on empirical data and methods, it allows us to consider the particularities of a specific area while exploring possible states that the system can reach after

the implementation of certain policy strategies. It does not mean that the model should provide a deterministic answer about the best policy approach to be adopted, as no model is able to consider all the relevant dimensions of a decision-making process. Still, the model is expected to provide new elements for stimulating debate, questions, critiques, and information exchange among stakeholders. It aims, therefore, to contribute to the development of better-informed urban policies.

In the MASUS model, the urban system is composed of two interrelated subsystems, the urban population and the urban landscape. At the micro-level of the urban population, *household agents* represent the residents of the city, which have their specific state and are periodically deciding to stay or to move to another residential location. At the macro-level, global segregation patterns emerge as an outcome of the household agents' decisions. Once an agent decides to move, it is contributing to a change in the spatial arrangement of social groups in the city, i.e., to its segregation levels.

The urban landscape is the environment where household agents are situated and where they act. It provides a spatially explicit context for the agents and is represented as a grid of *landscape cells*, with their own state and transitional dynamics (Feitosa *et al.*, 2011).

### **3.1 Process overview**

The operational MASUS model is implemented in NetLogo 4.1 (Wilensky, 1999) and its simulation protocol includes the following directives (Feitosa *et al.*, 2011):

- a. Set up the initial state of the system (Section 3.2).
- b. Start the annual cycle.
  - i. Execute the decision-making sub-model (Section 3.3).
  - ii. Calculate and report segregation indices (Section 3.4).
  - iii. Update population and landscape state for the next cycle (Section 3.5).

- iv. Update year ( $t^{+1}year = tyear + 1$ ) and repeat annual cycle.

### 3.2 Initial state of the system

The first step of the simulation, which sets up the initial state of the system, imports GIS data that represents the population and landscape state of the study area in the beginning of the simulation ( $t_0$ ). The current MASUS model is implemented for São José dos Campos (Fig. 1), a Brazilian city with a population of 629,921 (IBGE, 2010), and its initialization uses empirical data that replicates the characteristics of the city in 1991.



Fig. 1. Location of São José dos Campos, Brazil. The selected region corresponds to areas that are urbanized or subject to urban expansion.

Table 1 presents the variables that represent the state of household agents and landscape cells in the simulation. These variables are relevant either directly or indirectly to the locational behaviour of households. Since this relevance changes according to the empirical context that is being examined, their selection should take into consideration the results of residential mobility analyses for the study area (Section 3.3).

Table 1. State variables in the MASUS model.

Entity	State variable		Source
Household agent	INCOME	Income of the head of household (HoH)	Census data
	EDU	Education of the HoH	
	AGE	Age of the HoH	
	SIZE	Household size	
	KIDS	Presence of children	
	RENTER	Tenure status (1, if renter; 0, otherwise)	
Landscape cell	<i>Physical aspects:</i>		
	SLOPE	Terrain slope	Topographic map + GIS-based calculations
	URBAN	Urban occupation (1, if urbanized; 0, otherwise)	
	DWE	Number of dwellings	Landsat satellite images Census data
	INFRA	Infrastructure quality index (composed index representing the provision of water, sewage and garbage collection)	
	<i>Accessibility:</i>		
	CBD	Distance to the Central Business District	Zoning/Road maps + GIS-based calculations
	ROADS	Distance to roads	
	<i>Zoning legislation:</i>		
	ZPROT	Environmentally protected areas	Zoning map
	ZRES	Residential areas	
	ZMIX	Mixed-use areas	
ZIND	Predominantly industrial areas		
ZSOCIAL	Areas of social interest		
ZVACANT	Vacant urban land		
ZC	Central zone		
FAR	Floor area ratio		
<i>Real-estate market:</i>			
LVALUE	Land value	Property advertisements	
OFFER	Dwelling offers		
<i>Neighbourhood types:</i>			
TYPE A	Neighbourhoods with high land values and housing quality, good infrastructure and services, as well as many gated communities and apartment complexes.	Census data + aerial photos + official data on residential settlements (e.g., legal status) + fieldwork	
TYPE B	The most socially diverse type of neighbourhood. They are well served with infrastructure, and often concentrate many services and commercial activities.		
TYPE C	Neighbourhoods with a predominance of low-cost dwellings. Despite the poverty concentration, these areas have basic infrastructure and services. It includes social housing settlements.		
TYPE D	Irregular settlements, characterized by substandard housing and lack of tenure security and public investments.		

The initial population of agents represents the full population of the city, consisting of 106,591 households in 1991. These data were obtained from the Brazilian census (which provides universal micro data for this particular year), loaded as vector points and assigned to household agents.

The data used to represent the state of landscape cells were obtained from different sources, including the Brazilian census, maps provided by the local government, and satellite images and aerial photos. Since historical real-estate market information is not available from official sources, this data was collected from property advertisements in newspapers of the municipal archive. The total number of dwellings offered in each neighbourhood (N= 2590) and the average price of their m<sup>2</sup> in 1991 was taken as proxy for dwelling offers and land value. All data related to the urban landscape were loaded as raster or vector polygons and assigned to a grid of cells, where each cell measures 100 m by 100 m.

### **3.3 Decision-making sub-model**

After setting up the initial state of the system, it is possible to start the annual cycle, which is the main time loop of the simulation. The first procedure of the annual cycle is to *execute the decision-making sub-model*, responsible for the household's decision about moving to another residential location. By executing this sub-model, each agent calculates utilities for different alternatives (Section 3.3.1) and has a higher probability of selecting the one with the highest utility. While selecting residential alternatives, the household agent evaluates  $n$  locations from a valid set that excludes places without available dwellings. Since the model assumes that agents can consider the possibility, even if small, of living in any neighbourhood of the city, there is no restriction regarding the characteristics of the neighbourhoods selected to be evaluated.

After computing the agent's probability of choosing the residential alternatives, the sub-model executes a Monte Carlo simulation to select one of them. The household agent then performs the action that matches the selected alternative.

### 3.3.1 Nested logit probability

The probability function used in the decision-making sub-model and its reference parameters were obtained from the estimation of a three-level nested logit model - NLM (Fig. 2). The first level ( $i$ ) concerns the household decision about *moving* or *staying* and focuses on how personal attributes such as age and tenure status can influence the households' mobility. The second level ( $j$ ) focuses particularly on the *neighbourhood type choice*. Having decided to move, the household can choose between: (a) moving within its *current neighbourhood*, (b) moving to the *same type of neighbourhood*, e.g., from an irregular settlement to another one, and (c) moving to a *different type of neighbourhood*, e.g., from a diverse neighbourhood to a gated settlement. The neighbourhood types considered in the analysis are described in Table 1.

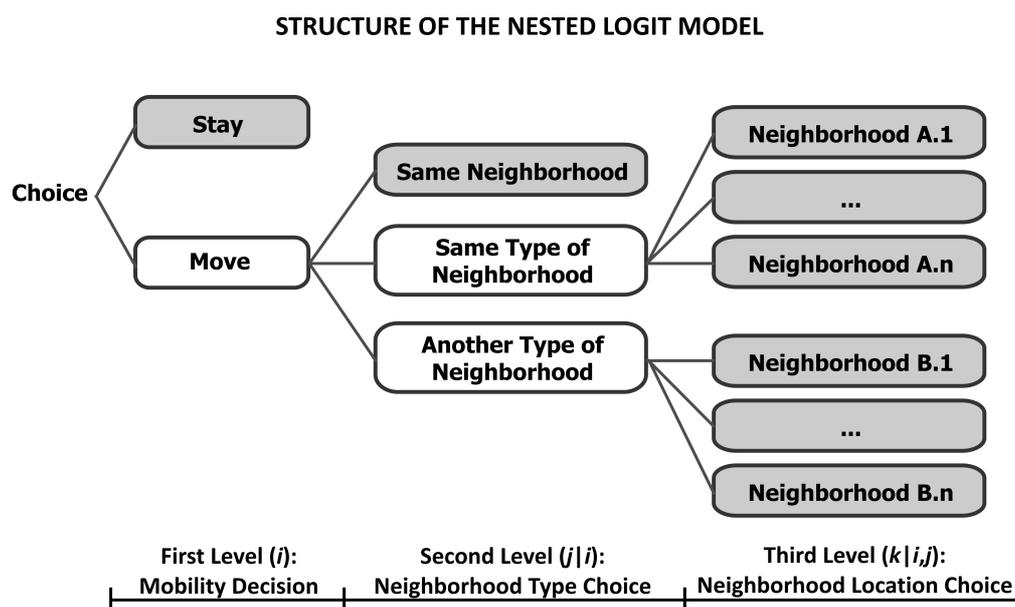


Fig. 2. Nested logit framework for the decision-making sub-model (Feitosa *et al.*, 2011).

The third level of the NLM ( $k$ ) concerns the *neighbourhood location choice* and complements the second level by including particular neighbourhood characteristics that may

influence the household choice for a certain location independently of the second-level alternatives (e.g., distance from the original residence).

Considering that  $X_{k|i,j}$ ,  $Y_{j|i}$  and  $Z_i$  refer to the vectors of explanatory variables specific to categories  $(k|i,j)$ ,  $(j|i)$ , and  $(i)$ , respectively, the probability of choosing a particular branch  $k$  in limb  $j$ , trunk  $i$  is (Greene, 2000):

$$Pr(k) = Pr(k|i,j) \cdot Pr(j|i) \cdot Pr(i) \quad (1)$$

The conditional probability  $Pr(k|i,j)$  and  $Pr(j|i)$  in Equation (1) are:

$$Pr(k|i,j) = \frac{\exp\left[\frac{1}{\tau_{j|i}}(\beta'X_{k|i,j})\right]}{\sum_n \exp\left[\frac{1}{\tau_{m|i}}(\beta'X_{n|i,j})\right]} \quad (2)$$

and

$$Pr(j|i) = \frac{\exp\left(\frac{1}{\tau_i}(\alpha'Y_{j|i} + \tau_{j|i}I_{j|i})\right)}{\sum_m \exp\left(\frac{1}{\tau_i}(\alpha'Y_{m|i} + \tau_{m|i}I_{m|i})\right)} \quad (3)$$

where  $I_{j|i}$  is the inclusive value for category  $(j|i)$ , which transfers information from the neighborhood location choice model (third level) to the neighborhood type choice model (second level). Formally,  $I_{j|i}$  is the log of the denominator of the conditional probability  $Pr(k|i,j)$ . The term  $\tau_{j|i}$  is a dissimilarity parameter that provides a summary measure of the degree of correlation among alternatives in the nest  $(j|i)$ . The term  $\tau_{j|i}I_{j|i}$  represents the

expected utility that the decision maker receives from the choice among the alternatives in nest ( $j|i$ ).

The probability of choosing  $i$ ,  $Pr(i)$ , is:

$$Pr(i) = \frac{\exp(\gamma'Z_i + \tau_i I_i)}{\sum_l \exp(\gamma'Z_l + \tau_l I_l)} \quad (4)$$

where

$$I_i = \ln \left( \sum_m \exp \left( \frac{1}{\tau_l} (\alpha'Y_{m|i} + \tau_{m|i} I_{m|i}) \right) \right). \quad (5)$$

To estimate the parameters of the probability function, we used a household survey of 7910 respondents (universe of 141,814 households) conducted in 2003 (NEPO, 2003). For each respondent, the survey provides information about the household's characteristics and its retrospective residential mobility history. Based on this data, it was possible to obtain the dependent variable of the NLM (residential choice) and household-specific variables. The neighbourhood-specific variables were obtained from the sources mentioned in Section 3.2 and Table 1.

Since this work evaluates income segregation, the variable "income of the head of the household (HoH)" was used to stratify the model estimation. Three income intervals were considered: up to 4 minimum wages (mw), from 4 to 10 mw, and more than 10 mw. Despite this income-based stratification, the heterogeneity of the families was considered through the inclusion of other variables in the model, such as education level and age of the HoH.

The selection of explanatory variables relied on hypotheses about the determinants of household mobility and neighbourhood choice (Table 2). For the first level, which concerns the choice of moving or not, the hypotheses focus on household characteristics that may influence mobility behaviour. The second and third levels of the NLM focus on how households assess the characteristics of potential residential locations. While the second level

considers the impact of these characteristics in terms of the neighbourhood type choice, the third level concerns their general impact on the location choice, regardless of the second-level alternatives. The coefficients of residential location variables were first estimated for the second-level alternatives. In case they were not significantly distinguishable among these alternatives, the variables were then considered in the third-level of the model as generic.

Table 2. Explanatory variables and hypotheses.

Variable	Hypothesis
<i>First level: Mobility decision</i>	
AGE	Mobility decreases as the <b>age of the head of the household</b> (HoH) increases.
RENTER	<b>Renters</b> have higher mobility rates than owner-occupiers.
RENTER* INCOME	<b>Renters with limited financial resources</b> are more vulnerable to housing insecurity and more likely to present higher mobility rates.
<i>Second and third level: Neighbourhood type and location choice (general hypotheses)</i>	
MOVE1 MOVE2 MOVE3	Families are more likely to stay in their current residence than to move (high moving costs). Thus, the estimated coefficients for the <b>alternative-specific constants for moving "within the same neighbourhood" (MOVE1), "to the same type of neighbourhood" (MOVE2), and "to another type of neighbourhood" (MOVE3)</b> are expected to have a negative effect on the household's utility.
DIST	Households prefer to move to places with smaller <b>distance to the original place of residence</b> in order to keep their social bonds.
LVALUE/ INCOME	Households usually choose to spend a smaller portion of their income on housing.
OFFER	New investments in housing (more <b>dwelling offers</b> ) attract residents and consolidate residential expansion vectors.
CBD	Smaller <b>distances to the Central Business District</b> increases the attractiveness of neighbourhoods.
<i>Second and third level: Neighbourhood type and location choice (income-group specific hypotheses)</i>	
LOWER MIDDLE HIGHER	Households tend to choose places with a higher proportion of neighbours belonging to their income group. Thus, variables representing the <b>proportion of income groups in the neighbourhoods</b> were included in the model of the respective group.
TYPEA TYPEB TYPEC TYPED	Higher-income families are more likely to choose <b>type A or B</b> neighbourhoods; middle-income are more likely to choose <b>type B</b> ; and lower-income are more likely to choose <b>type C or D</b> .
TYPEB*EDU TYPED*EDU	Lower-income families with a better <b>educated HoH</b> have a higher chance to move to <b>type B</b> neighbourhoods, and a smaller chance to move to irregular neighbourhoods ( <b>type D</b> )
TYPEC* INFRA	Middle-income families may move to poorer neighbourhoods ( <b>type C</b> ) if the area provides good <b>infrastructure</b> and services.
TYPEA* KIDS	Higher-income families with <b>children</b> are more likely to choose <b>type A</b> neighbourhoods, given the security-related appeal of gated communities.

The coefficients of the NLM were estimated with respect to the choice "stay" and the results are presented in Table 3.

Table 3. NLM coefficients adopted as reference for the probability function of the decision-making model.

Level	Choice	Variable	Coefficients - Income groups		
			Lower-Income	Middle-Income	Higher-Income
1 <sup>st</sup>	Move	AGE	-0.043 ***	-0.046 ***	-0.040 ***
		RENTER	3.080 ***	2.243 ***	2.542 ***
		RENTER*INCOME	-1.2(10 <sup>-3</sup> ) ***	NS	NS
2 <sup>nd</sup>	Move within the same neighbourhood	MOVE1	-1.592 **	-2.123 ***	-2.532 ***
		OFFER	NS	NS	
		CBD	NS		
		LOWER	NS		
	Move to the same type of neighbourhood	MOVE2	-3.810 ***	-2.631 ***	-2.464 ***
		OFFER	1.9(10 <sup>-3</sup> ) ***	1.9(10 <sup>-3</sup> ) ***	
		CDB	6.7(10 <sup>-5</sup> ) **		
		LOWER	0.953 *		
		TYPEA			NS
		TYPEB		NS	NS
		TYPEC	NS	NS	
		TYPED	NS		
		TYPEB*EDU	NS		
		TYPED*EDU	NS		
	TYPEC*INFRA		NS		
	TYPEA*KIDS			NS	
	Move to the another type of neighbourhood	MOVE3	-6.163 ***	-2.451 ***	-3.457 ***
		OFFER	3.0(10 <sup>-3</sup> ) ***	1.9(10 <sup>-3</sup> ) ***	
		CDB	10.3(10 <sup>-5</sup> ) **		
		LOWER	1.520 *		
		TYPEA			NS
TYPEB			NS	NS	
TYPEC		2.379 **	NS		
TYPED		2.254 *			
TYPEB*EDU		0.195 **			
TYPED*EDU		NS			
TYPEC*INFRA		NS			
TYPEA*KIDS			1.49 **		
3 <sup>rd</sup>	Generic variables	DIST	-1.3(10 <sup>-4</sup> ) ***	-11.1(10 <sup>-5</sup> ) ***	-4.9(10 <sup>-5</sup> ) **
		LVALUE/INCOME	NS	-0.04 *	NS
		OFFER			1.4(10 <sup>-3</sup> ) ***
		CBD		NS	NS
		MIDDLE		1.435 *	
		HIGHER			0.960 **
Dissimilarity parameters		$\tau$ -move (first level)	0.658 *	0.752 **	0.666 *
		$\tau$ -move2 (second level)	0.449 **	0.292 *	0.384 *
		$\tau$ -move3 (second level)	0.791 *	0.453 *	0.552 *

\*\*\*, \*\*, and \* indicate statistical significance at the 99%, 95%, and 90% levels. NS indicates no statistical significance.

### 3.4 Segregation indices

After executing the decision-making sub-model, the next procedures of the annual cycle are to *calculate* and *report segregation indices*. The MASUS simulation outputs are monitored through global and local segregation indices. Global indices summarize the segregation degree of the whole city, while local indices depict segregation as a spatially variant phenomenon and are shown as maps. The model reports two spatial segregation indices (Feitosa *et al.*, 2007):

- a. Spatial dissimilarity index: Its global version ( $D$ ) measures how the population composition of each neighbourhood differs, on average, from the population composition of the whole city. It varies from 0 to 1 (maximum segregation). The local version of this index ( $d_j$ ) shows how much each neighbourhood contributes to the global  $D$  measure of the city.
- b. Spatial isolation index of group  $m$ : Its global version ( $Q_m$ ) measures the average proportion of group  $m$  in the neighbourhood of each member of this group. It ranges from 0 to 1 (maximum isolation) and its values depend on the overall population composition of the city. For example, if there is an increase in proportion of group  $m$  in the city, the value of  $Q_m$  tends to become higher. The index  $Q_m$  also presents a local version ( $q_{m,j}$ ).

### 3.5 Additional sub-models

After reporting the simulation outputs, the program executes sub-models that *update the population and landscape state for the next cycle*. To update the population state, complementary bottom-up and top-down sub-models are executed: the household transition and the population transition. The household transition sub-model relies on a set of rule-based

functions that simulate certain household events (e.g., aging or dissolution). It is complemented by the population transition sub-model, which is responsible for keeping the growth and socio-demographic composition of the population according to annual control variables defined by the modeller. It creates households with profiles that meet the expected composition of the population (Feitosa *et al.*, 2011).

Four sub-models are executed to update the following aspects of the system's landscape state: urban sprawl, land value, dwelling offers and infrastructure. The *urban sprawl sub-model* simulates the expansion of the urbanized areas in the city. Its first phase employs Markov chain methods to quantify the sprawl, while the second relies on logistic regression probabilities to allocate the new urban cells. The *dwelling offers sub-model* relies on rule-based functions and regression models to update the number of dwellings in each cell. The *land value sub-model* uses hedonic price models to estimate the land value of cells, while the *infrastructure sub-model* estimates the infrastructure quality of each cell using linear regression models (Feitosa *et al.*, 2011). The specification of these sub-models and the empirical calibration of their parameters are presented in Feitosa (2010).

After updating the population and landscape state, the program repeats the annual cycle.

## **4 Exploring anti-segregation strategies: spatial dispersal of poverty vs. spatial dispersal of wealth**

### **4.1 Experiment design**

To assess the impact of different social-mix policy approaches, three different scenarios were simulated in MASUS: baseline scenario, spatial dispersal of poor families, and spatial dispersal of wealthy families. To evaluate these scenarios, global and local

versions of three spatial segregation indices (Section 3.4) were computed for each simulated time step: spatial dissimilarity ( $D$  and  $d_j$ ), spatial isolation of low-income households ( $Q_{low}$  and  $q_{low,j}$ ), and spatial isolation of high-income households ( $Q_{high}$  and  $q_{high,j}$ ). Since previous multi-scale analyses of São José dos Campos' segregation revealed distinct spatio-temporal trends when computing these indices for different scales of neighbourhood (Feitosa *et al.*, 2007), the present study considered two representative neighbourhood scales for monitoring the simulation outputs: (a) a local scale, where the household's neighbourhood comprises the area within a 700 m radius of its residence location, a distance that can be easily covered on foot, and (b) a large scale, where this radius is equal to 2000 m.

#### **4.1.1 Baseline scenario**

The baseline scenario is used as reference for evaluating the relative impact of anti-segregation policies. The intent of this scenario is to reproduce the segregation dynamics of São José dos Campos during the periods 1991-2000 and 2000-2010. The initial state of the experiment replicates the characteristics of the city as described in Section 3.2.

A baseline scenario for the period 1991-2000 was previously presented by Feitosa *et al.* (2011), when 9 simulation annual cycles were executed and compared with real data for the year 2000. This comparison was conducted in terms of the spatial distribution of income groups, i.e., the change in the magnitude of the overall segregation revealed by the global segregation indices and in the spatial segregation patterns revealed by the local indices maps.

Despite the satisfactory results originally achieved with the parameters estimated from statistical models (Section 3.3.1), a calibration consisting of small changes in some parameters of the decision-making sub-model improved the fit between the simulated and real data. These changes concerned the parameters estimated for the variables representing

the proportion of neighbours belonging to each income group (LOWER, MIDDLE and HIGHER).

For the experiments presented in this paper, it was also necessary to simulate a baseline scenario for 2000-2010, which adopted the same decision-making parameters calibrated for the previous period.

#### 4.1.2 Policy experiment I: Spatial dispersal of poor families

The scenarios simulating the spatial dispersal of poor families test the effect of a social-mix policy that moves poor households out of distressed areas by distributing housing vouchers. In the experiment, poor families that are randomly selected from locations with high isolation of poverty receive housing vouchers for renting dwellings in neighbourhoods in which the isolation of poor families is below the average. For the period 1991-2000, the experiment consists of simulating two scenarios with progressive distribution of housing vouchers: from 200 to 1700 vouchers and from 500 to 4200 vouchers (Fig. 3a). For the period 2000-2010, the two simulation runs kept a constant investment in the housing program: 1700 and 4200 vouchers (Fig. 3b).

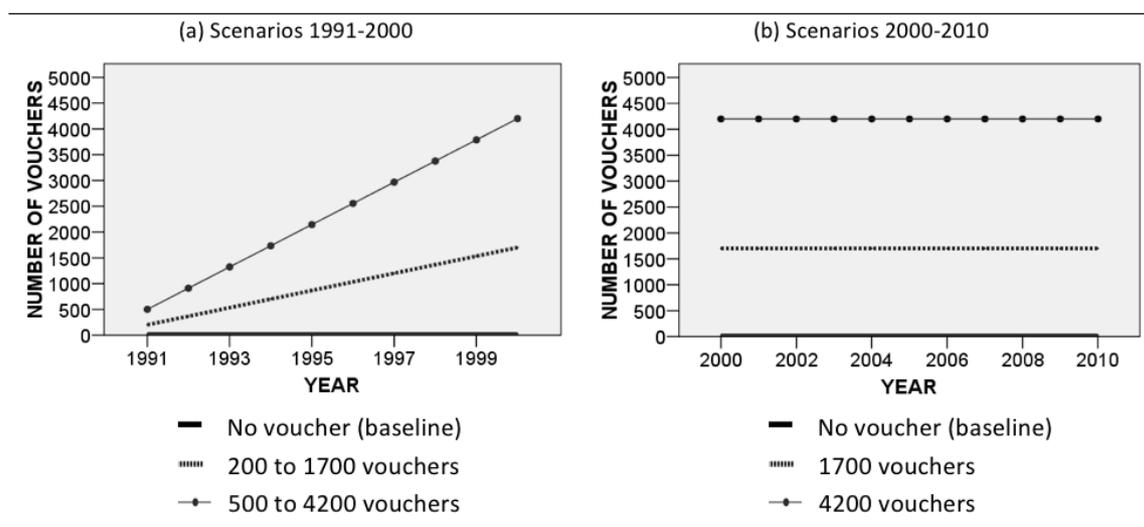


Fig. 3. Scenarios of the experiment on spatial dispersal of poverty: number of housing vouchers distributed during the periods 1991-2000 and 2000-2010.

### **4.1.3 Policy experiment II: Spatial dispersal of wealthy families**

The scenario simulating the spatial dispersion of wealthy families assumes the successful implementation of policies that address the dynamics of the real estate market by stimulating the construction of residential developments for middle and upper classes in poor regions of the city. In practice, these policies represent a challenging task, as they should include a diversified set of measures, such as concessions, tax exemptions, changes in land-use norms, as well as investments in security, local facilities, and infrastructure.

To conduct the experiment, some undeveloped areas located in poor regions of the city were identified from orthophotos and, in the model, the state variables concerning the "neighbourhood type" of the landscape cells corresponding to these areas were pre-defined as "type A" (Table 1), i.e., settlements designed for residential occupation of middle and upper classes, with good housing quality, infrastructure and services. Considering the pre-established conditions for the development of these settlements, a simulation run was executed for the period 1991-2010.

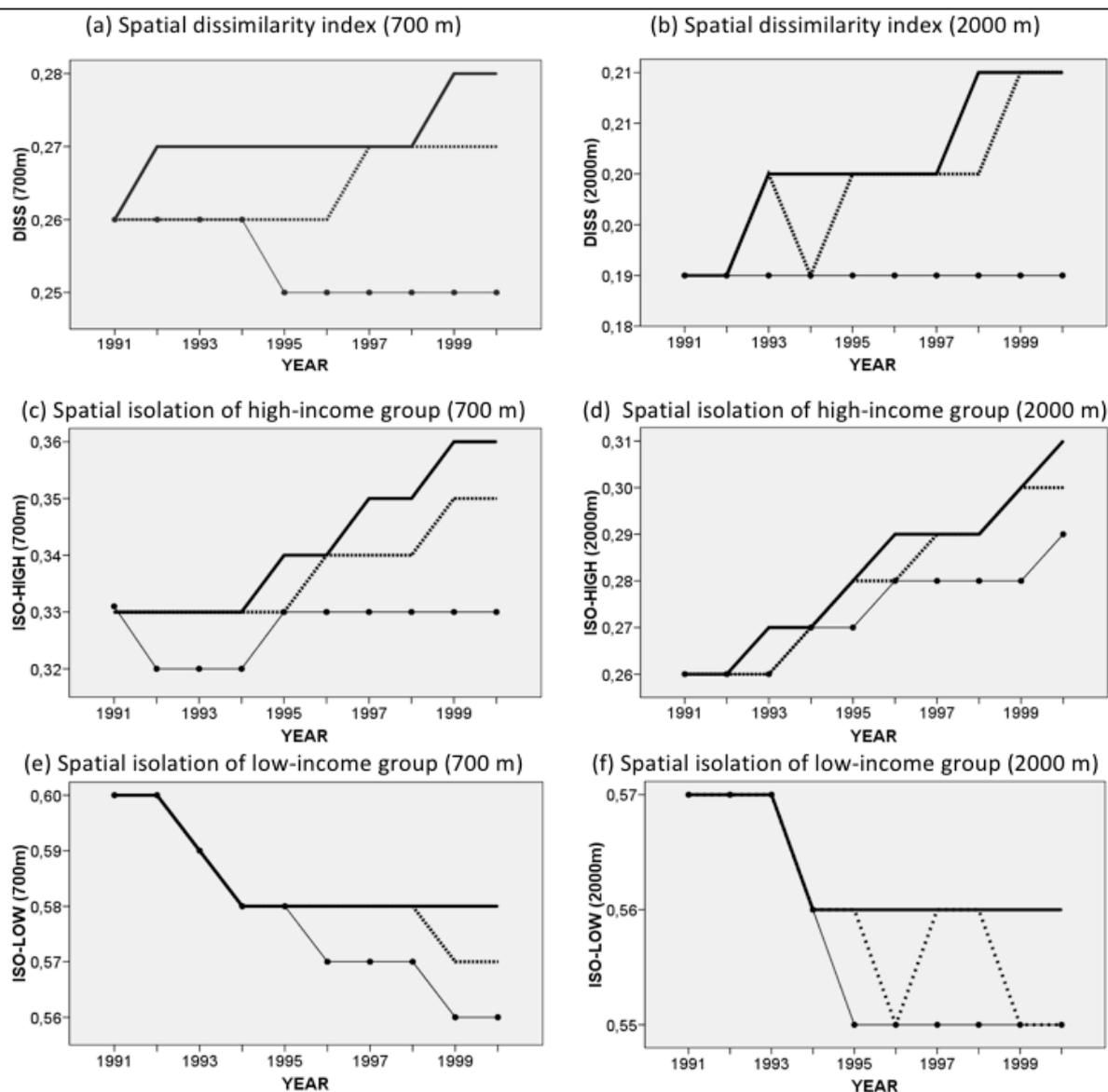
## **4.2 Results and discussion**

### **4.2.1 Impact of policies based on the spatial dispersal of poor families**

#### ***Period 1991-2000: Increasing number of housing vouchers***

The graphs in Fig. 4 present the progression of global segregation indices during the period 1991-2000 for three simulated scenarios: baseline (no housing voucher), alternative 1 (200 to 1700 vouchers), and alternative 2 (500 to 4200 vouchers). The graphs show indices computed for different scales of neighbourhood (neighbourhood radius equal to 700 m and 2,000 m). For each experiment, at least five replications were performed and, despite the stochastic nature of the model, all the replications produced the same results.

**Spatial dispersal of poverty: Global Segregation Indices, Period 1991-2000**  
**700-m and 2000-m neighbourhood radius**



Scenarios: — No voucher (baseline)      ..... Alternative 1: 200 to 1700 vouchers      —●— Alternative 2: 500 to 4200 vouchers

Fig. 4. Progression of global segregation indices (700-m and 2000-m neighbourhood radius) for the scenarios 1991-2000 on poverty dispersal.

The global dissimilarity index  $D$  computed for a local neighbourhood scale (700 m), which in the baseline scenario increased from 0.26 to 0.28 in the period 1991-2000, increased to 0.27 in the first alternative scenario (Fig. 4a). In this scenario, the distribution of 1,700

vouchers, which benefit 2.3% of the low-income households in the year 2000, caused a decrease of 3.5% in the dissimilarity index. In the second alternative scenario, the distribution of vouchers to 5.8% of the low-income households (4200 vouchers) decreased the dissimilarity index by 10.7%.

The positive impact of distributing vouchers was less significant for larger neighbourhood scales (Fig. 4b). In the baseline scenario, the global dissimilarity index  $D$  computed for a 2000-m neighbourhood radius increased from 0.19 to 0.21 during 1991-2000. Compared with the baseline run, the first alternative scenario presented equal or slightly lower dissimilarity indices, whereas the second alternative presented constant levels of dissimilarity during the period (0.19).

The global indices of isolation demand a careful evaluation, since their values are influenced by the proportions of the income groups in the city. During the period 1991-2000, the proportion of high-income households (more than 10 minimum wages) increased from 0.15 to 0.19, and their spatial isolation computed for a 700-m neighbourhood radius increased from 0.33 to 0.36 in the baseline scenario (Fig. 4c). This last result means that, on average, 36% of the neighbours of a high-income household belonged to the same income group in 2000. This value is much higher than the overall percentage of this group in the city (19%).

As presented in Fig. 4c and 4d, the spatial isolation index of high-income families decreased significantly in both scales (700-m and 2000-m) as the investment in the housing program increased. For example, the distribution of housing vouchers to 5.8% of the low-income (4200 vouchers) caused a decrease of 8.3% in the isolation of high-income households measured at the local scale (from 0.36 to 0.33). Regarding the isolation level of low-income households, however, the impacts of the housing program were disappointing. The distribution of vouchers to 5.8% of the low-income households decreased the isolation of this group by only 3.4% (from 0.58 to 0.56, Fig. 4e). The contribution of the policy regarding

decreasing the isolation of low-income households was even less significant when the analyses rely on the index computed for larger neighbourhoods (Fig. 4f). In this case, the distribution of 1700 vouchers (alternative 1) did not decrease the isolation of low-income households, whereas the distribution of 4200 vouchers (alternative 2) decreased the isolation by only 1.8%. This represents a relevant drawback of the voucher policy, as the isolation of low-income households is the segregation dimension that has the most harmful impacts on the lives of disadvantaged people.

### ***Period 2000-2010: Constant number of housing vouchers***

The graphs in Fig. 5 present global segregation indices obtained from the experiments on poverty dispersal for the period 2000-2010, which kept the distribution of housing vouchers constant over the years. In these experiments, the baseline scenario 2000-2010 is compared with two alternative scenarios in which 1700 and 4200 vouchers were distributed. The results show that this continued investment only slows the increase in segregation, as it was unable to modify the segregation trends in comparison with the baseline scenario.

These results reveal that, in developing-country cities, where low-income families represent a larger share of the population, policies based on the distribution of vouchers require high and continuous investments to produce a significant change in the overall segregation levels of the city. Such amount of investment is usually unfeasible for these cities. Nevertheless, the benefit of moving poor families out of distressed areas can bring other benefits that are not related with the segregation levels of the city as a whole. Rather, these benefits could be related to personal experiences of families who received the vouchers, including the access to a set of advantages able to enhance their opportunity structure, with impacts on both current and future generations. These advantages include better quality of built and natural environment, greater diversity in the neighbourhood social network, better

access to different sources of information, improved educational and employment opportunities, and reduced vulnerability to crime. In this sense, the spatial distribution of poverty can be seen as a “people-based” strategy.

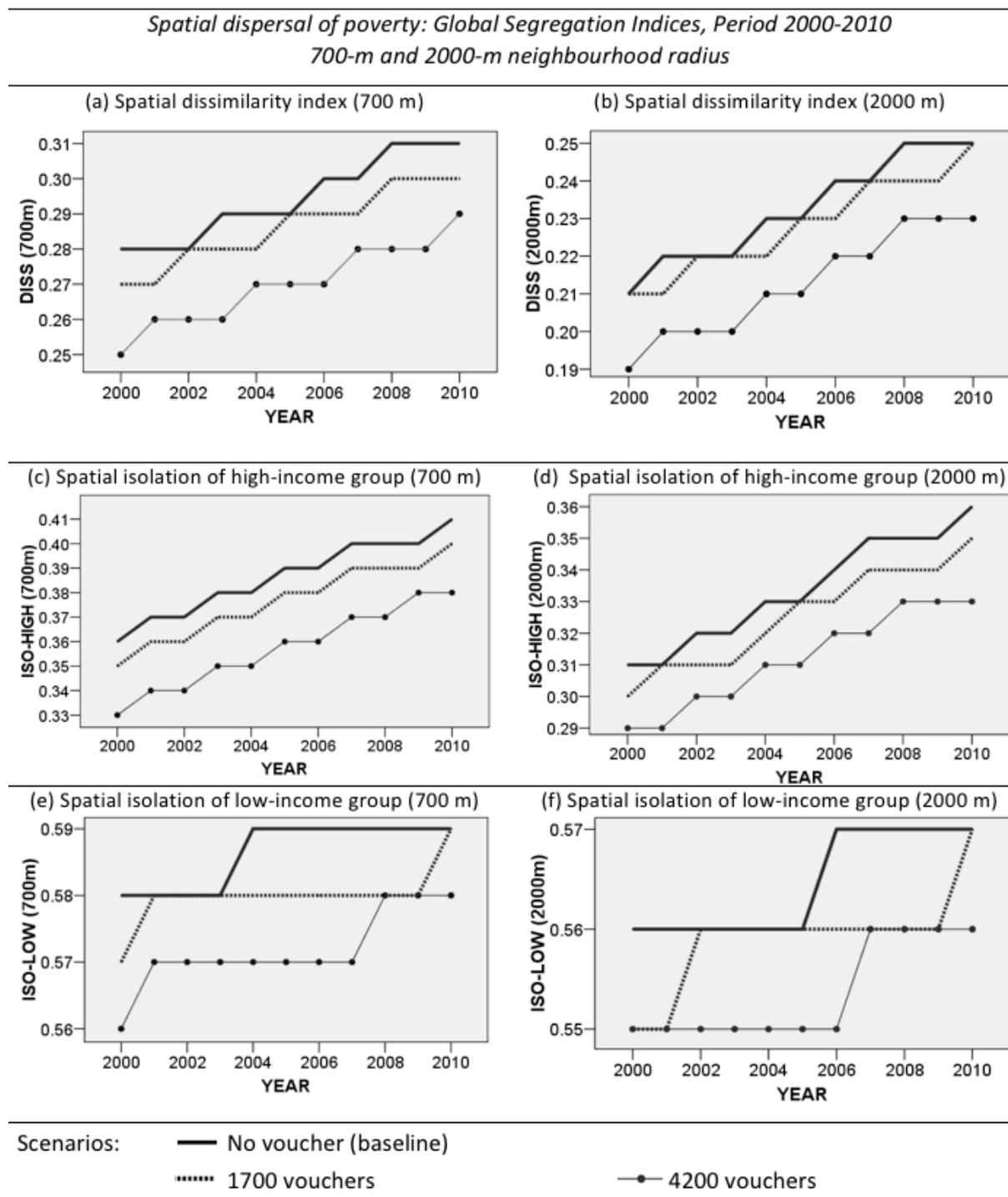


Fig. 5 Progression of global segregation indices (700-m and 2000-m neighbourhood radius) for the scenarios 2000-2010 on poverty dispersal.

In Brazil, where housing policies follow the national culture of homeownership, measures based on voucher distribution are seldom implemented. Some initiatives in this direction can be found, but none focuses on decreasing segregation. They are mostly adopted as a temporary alternative for emergency situations (e.g., dwellings destroyed by natural disasters) or for relocating families living in areas at imminent risk. Due to the low value of the voucher, families often move to other problematic neighbourhoods, with high levels of poverty concentration. In addition, as the distribution of vouchers is implemented for a limited period, usually no longer than 30 months, the families who receive the benefit remain in a situation of uncertainty and vulnerability.

#### **4.2.2 Impacts of policies based on the spatial dispersal of wealthy families**

A simulation run considering the development of new settlements for middle and upper classes in poor regions of the city was executed for the period 1991-2010 and the results compared with the baseline scenario. Fig. 6 presents the graphs comparing the global segregation indices of these scenarios along the years. In general, it can be observed that the policy approach based on wealth dispersal produces long-term outcomes. The consolidation of the new areas designated for upper classes may take some years, and therefore their positive impacts on the global segregation indices become more substantial with time. This is an advantage in comparison with the poverty dispersion policy tested in Section 4.2.1, which demands a continued public investment for housing vouchers. As soon as this investment ceases, its positive impact on segregation cannot be sustained.

**Spatial dispersal of wealth: Global Segregation Indices, Period 1991-2010**  
**700-m and 2000-m neighbourhood radius**

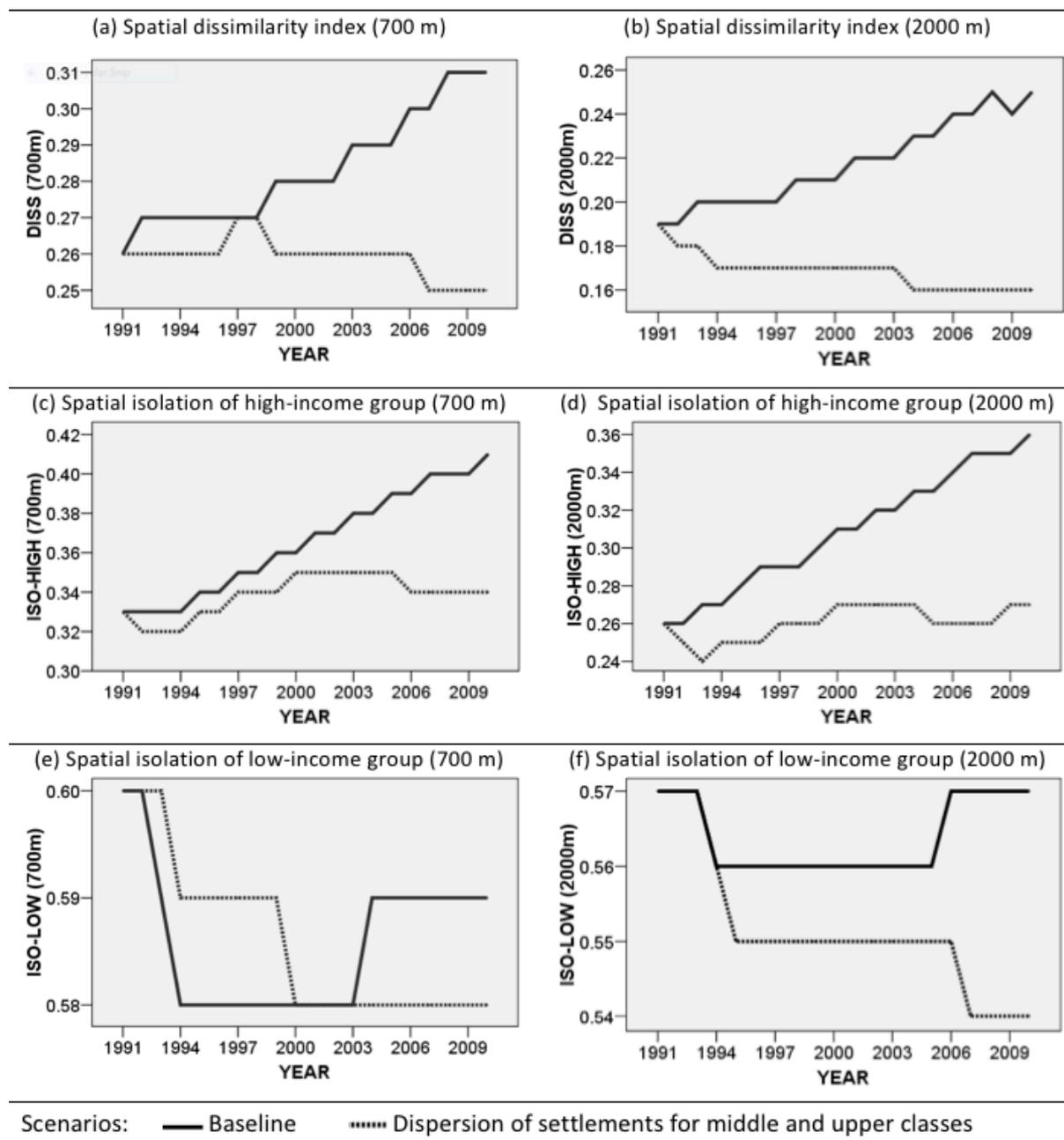


Fig. 6 Progression of global segregation indices (700-m and 2000-m neighbourhood radius) for the scenario 1991-2010 on wealth dispersal.

The global segregation indices presented in Fig. 6 and Table 4 indicate that the dispersion of wealthy families tends to be more effective towards decreasing large-scale segregation. For example, the dissimilarity index computed for a local scale for the year 2010

(700-m neighbourhood radius) decreases 19% when the policy based on wealth dispersion is adopted, which is less than the decrease of 36% that is observed when the same index is computed for a large scale (2000-m neighbourhood radius). The same effect occurs for the other indices: the isolation of affluent households in 2010 decreases 17% at the local and 25% at the large scale, whereas the isolation of low-income households decreases only 1.7% at the local scale, but 5.3% at the large scale. This outcome represents another advantage in comparison with the approach based on poverty dispersal (Table 4): Segregation at larger scales, particularly the concentration of poverty, is considered more damaging than segregation at local scales (Sabatini *et al.*, 2001).

Table 4. Global segregation indices 2010 (700-m and 2000-m neighbourhood radius) for three scenarios: baseline (BAS), spatial dispersal of poverty – 4200 vouchers (SDP), and spatial dispersal of wealth (SDW).

**Spatial Dispersal of Poverty (SDP) vs. Spatial Dispersal of Wealth (SDW)**  
**Global segregation indices - year 2010**

	Local-scale segregation 700-m neighbourhood radius			Large-scale segregation 2000-m neighbourhood radius		
	<b>BAS</b>	SDP	SDW	<b>BAS</b>	SDP	SDW
Spatial dissimilarity ( $\bar{D}$ )	<b>0.31</b>	0.29 (↓ 6.5%)*	0.25 (↓ 19%)	<b>0.25</b>	0.23 (↓ 8.0%)	0.16 (↓ 36%)
Spatial isolation of high-income families ( $\bar{Q}_{rich}$ )	<b>0.41</b>	0.38 (↓ 7.3%)	0.34 (↓ 17%)	<b>0.36</b>	0.33 (↓ 8.3%)	0.27 (↓ 25%)
Spatial isolation of low-income families ( $\bar{Q}_{poor}$ )	<b>0.59</b>	0.58 (↓ 1.7%)	0.58 (↓ 1.7%)	<b>0.57</b>	0.56 (↓ 1.8%)	0.54 (↓ 5.3%)

Scenarios: BAS = Baseline; SDP = Spatial Dispersal of Poverty (4200 vouchers);

SDW = Spatial Dispersal of Wealth.

\* Percentage of decrease in segregation levels, comparing with the baseline scenario.

The local version of the segregation indices complement the analyses by showing where are the most segregated areas in the city and how spatial patterns of segregation can change with the implementation of social-mix policies. Fig. 7 shows local segregation indices (2000-m neighbourhood radius) computed for three simulated scenarios for the year 2010:

baseline, spatial dispersal of poverty (4200 vouchers) and spatial dispersal of wealth. These indices are presented as maps, with darker colours representing higher levels of segregation.

***Spatial dispersal of poverty vs. Spatial dispersal of wealth: Local Segregation Indices  
Year 2010, 2000-m neighbourhood radius***

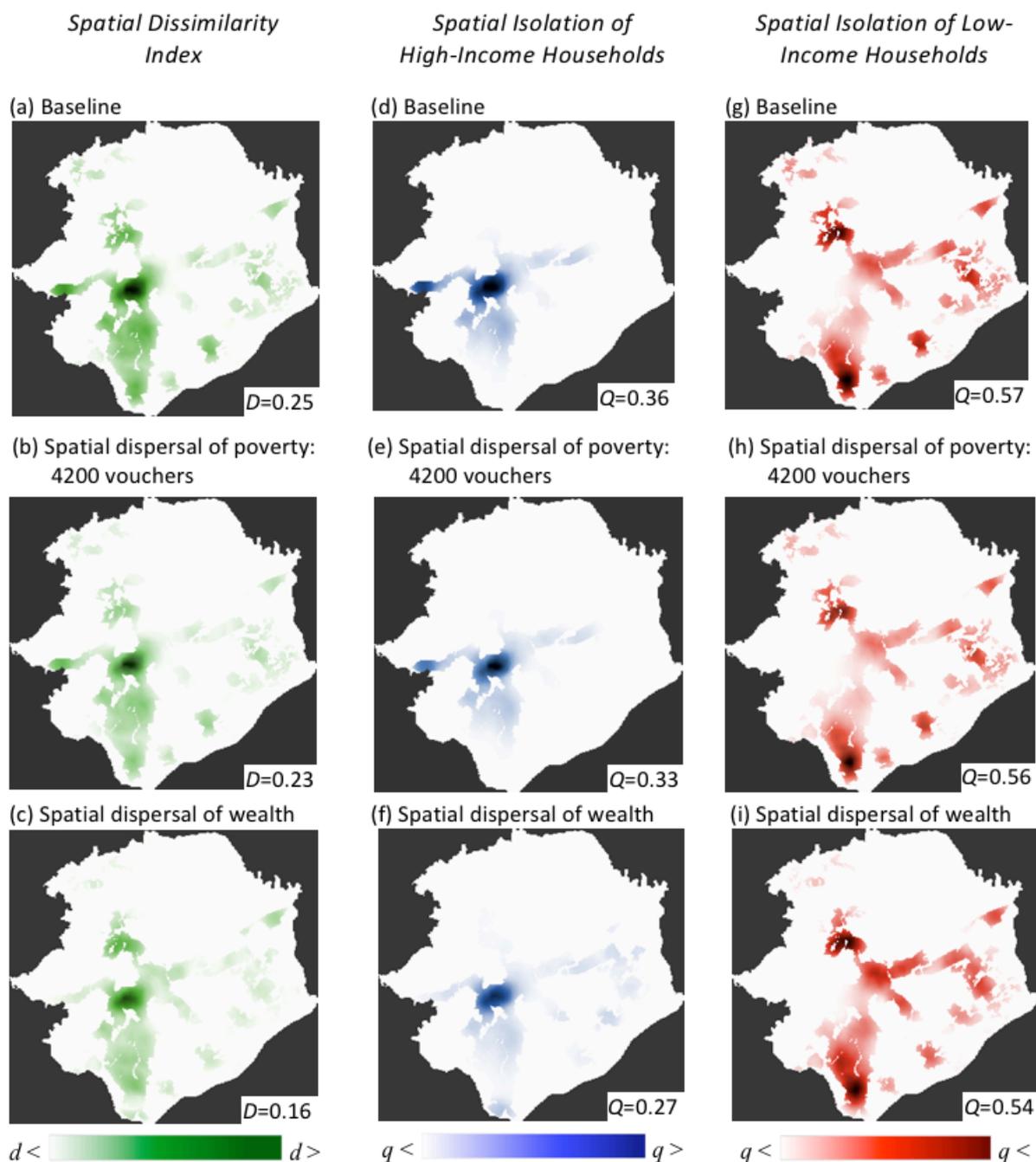


Fig. 7 Local indices of segregation (2000-m neighbourhood radius) for three simulation scenarios for the year 2010: baseline, spatial dispersal of poverty and spatial dispersal of wealth. Darker colours represent higher levels of segregation.

In general, the maps of the local version of the dissimilarity index show a higher level of dissimilarity in the central region of the city (Fig. 7a-c). The isolation maps complement this information by indicating that the dissimilarity hot spot in the central area is caused by the concentration of high-income households (Fig. 7d-f). The isolation of low-income households, on the other hand, presents a different spatial pattern, characterized by several hot spots located in different areas of the city (Fig. 7g-i).

The local segregation indices also indicate that the simulated wealth-dispersal policy was the most effective on modifying spatial patterns of dissimilarity and isolation of high-income households. First, the local dissimilarity indices became smoother and spread throughout the city (Fig. 7c). Second, the isolation pattern of high-income households, which appeared in the baseline scenario as a consolidated axis starting from the central area of the city towards the western region (Fig. 7d), became spatially diffuse throughout the city (Fig. 7f). This spatial trend presented in the wealth dispersal scenario is positive, as affluent residents are more likely to circulate through different parts of the city and increase their contact with distinct social groups and realities (Villaça, 1998). In addition, poor families located near residential projects for upper classes often benefit in terms of employment, quality of services, and urban facilities (Sabatini, 2006; Sabatini *et al.*, 2001).

## 5. Conclusions

Urban segregation is one of the most outstanding features of Brazilian cities, with impacts that have been reinforcing the social exclusion of disadvantaged families. Developing policies that effectively minimize segregation and its negative outcomes is a challenging task that depends on a better understanding of local particularities of segregation dynamics. This paper uses the model MASUS, Multi-Agent Simulator for Urban Segregation, to explore the impact of urban policies on the segregation dynamics of São José dos Campos.

MASUS provides a virtual laboratory for supporting experiments that address the complex nature of segregation and considering particular features of the study area. These experiments do not aim to provide deterministic answers or policy panaceas, i.e., universal and simple solutions to be applied in different circumstances (Ostrom *et al.*, 2007). Instead, their purpose is to raise new questions, ideas and insights for a continuous learning process on the development of urban policies that promote a more integrated city.

Contributing to this aim, this paper tested two different social-mix strategies: one based on the spatial dispersal of poverty, and the other on the spatial dispersal of wealth. In cities like São José dos Campos, where, in comparison with cities in developed countries, low-income families represent a large proportion of the population, these strategies revealed different benefits and shortcomings. The distribution of housing vouchers, which promotes the spatial dispersal of poverty, has the advantage of generating immediate results but demands intensive and continuous investment to produce significant changes in the segregation levels of the whole city. As soon as the voucher distribution ceases, its positive impact on segregation cannot be sustained. This feature is particularly problematic in Brazil, where housing policies focus on homeownership, and voucher-based measures are seen as merely temporary solutions for emergency situations.

The spatial dispersal of wealthy families relies on implementing measures that stimulate the construction of residential areas for middle and upper classes in poor regions of the city. Unlike the policy based on poverty dispersal, this one generates long-term results, as the consolidation of new settlements typically requires several years. As time passes, the positive impact of dispersing wealth becomes more expressive and less dependent on public investments. Nevertheless, finding a combination of incentives that successfully promotes the establishment of wealthy settlements in poor areas remains a challenge.

The results of these experiments also revealed that the wealth-dispersal policy was more effective in stimulating positive changes in the overall levels and patterns of segregation. The policy promoted an expressive decrease in large-scale segregation and a more diffuse isolation pattern of affluent households. This is another advantage of the wealth dispersal strategy in relation to the approach based on distributing housing vouchers, which was less effective with regard to modifying ongoing segregation trends. Nevertheless, the poverty-dispersal policies have merits that complement those based on wealth dispersal, as these policies introduce benefits to the families who receive vouchers, can improve their opportunity structure, and positively affect the lives of current and future generations.

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