ALFONSO COSENZA

Location of relief supplies warehouses for Sao Paulo state Civil Defense

Graduation work presented at Escola Politècnica da Universidade de São Paulo for the accomplishment of the “Diploma de Engenheiro de Produçao”

Advisor: Associate Professor Hugo Tsugunobu Yoshida Yoshizaki

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The conclusion of this work also coincide with the conclusion of my wonderful experience at Polytechnic School of the USP.

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ABSTRACT

Brazil is one the state with the largest number of people affected by natural disaster, São Paulo state in particular is strongly affected by floods and landslides. Each year Civil Defense performs hundreds of interventions, providing support to the people affected.

Being prepared to face a disaster is fundamental to limit its impact on the society.

A optimal prepositioning of the relief supplies can make the difference. However the choice is always a tradeoff between costs and operation efficiency. This work will try suggest a solution to the problem.

The distribution of people living in risk condition is studied, collecting data from municipal preparatory plans an Civil Defense historic of interventions.

For the cities not owning a preparatory plan with a mapping of risk, the number of people living in risk condition has been predicted through the use of generalized linear models. Data about interventions and people affected, together with demographic data have been linked to the number of people living in risk condition.

The distribution of people at risk has been used to estimate the annual demand of rielief supplies, and this data used as input for a stochastic optimization model. In the model real data of distance and travel time between candidate locations and the demand point has been used in order to take into account the road quality and the state topography.

The model estimates the best location for the relief supplies deposits and allows to compare it to the current configuration.

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ABBREVIATIONS AND ACRONYMS

CBH-RB	Comitê da Bacia Hidrográfica do Ribeira de Iguape e Litoral Sul
CEDEC	Coordenadoria Estadual de Defesa Civil
COMDEC	Coordenadoria Municipal de Defesa Civil
CPRM	Serviço Geológico do Brasil
CRED	Centre for Research on the Epidemiology of **Disasters**
EM-DAT	The OFDA/CRED International Disaster Database.
EVPI	Expected Value of Perfect Information
FEMA	Federal Emergency Management Agency
GLM	Generalized Linear Model
IBGE	Instituto Brasileiro de Geografia e Estatística.
IG	Instituto de Geociências da USP
IFRC	International Federation of Red Cross and Red Crescent Societies
IPT	Instituto de Pesquisas Tecnológicas do Estado de São Paulo.
MIP	Mixed Integer Programming
OFDA	Office of U.S. Foreign Disaster Assistance
OSRM	Open Source Routing Machine
REDEC	Coordenadoria Regional de Defesa Civil
VSS	Value of the Stochastic Solution

SUMMARY

1. INTRODUCTION

1.1. OBJECTIVE

This graduation work objective can be resumed in answering the following question:

“In the São Paulo State, where should be located the relief supplies deposits for disaster response?”

Developed in collaboration with the Center for Innovation in Logistics System of the Polytechnic School of the University of São Paulo (CISLOG), this project is directed to the São Paulo State Coordinating Body of Civil Defense, in Portuguese “Coordenadoria Estadual da Defesa Civil do Estado de São Paulo” (CEDEC-SP). This organization is responsible for the humanitarian aid supply chain directed municipalities in abnormality situations, usually declared after the eventuality of being affected by natural disasters.
The focus of the thesis is to analyses the vulnerability to natural disaster of the population of the São Paulo state and by means of stochastic cost minimization model present a set of possible location for the CEDEC relief supplies warehouses.

During to development of the work, in order to implement the mathematical model, the following steps have been considered:

- The Civil Defense historic series of intervention has been aggregated and analyzed, the interventions classified, according to the geographic localization of the intervention and kind of hazard.
- The municipal disaster preparatory plans and risk mappings have been analyzed and data about houses in risk condition aggregated. Starting from this information the number people living in a situation of risk has been estimated.
- Generalized linear regression multivariable models have been developed in order connect historic data of intervention of the Civil Defense and demographic

information to data on the number to people vulnerable to natural disaster coming from municipal preparatory plans. Through these models, the number of people at risk in the cities not owing a preparatory plan have been estimated.

- The data about distance and travel time between the possible warehouse locations have been collected using online routing services.
- The transportation cost and capacity parameters, attendance coverage

The choose of a cost minimization model is justified by the fact that, differently that in disaster response phase, where the main objective is to save as many life as possible, in preparation to phase budget has be taken into high consideration, especially in actual Brazilian economic situation.

The expected result of this work is to offer to the Civil Defense decision makers a support in such delicate choice, and to be a base technical support to the budget draft to be presented to the São Paulo State Government for Civil Defense's logistic network restructuration plan. Furthermore, with this work is expected to enrich the academic literature regarding humanitarian aid logistic, a still too poor stream, especially in Brazil.

2. LITERATURE REVIEW

2.1. DISASTERS, CIVIL DEFENSE AND HUMANITARIAN LOGISTIC

2.1.1. GENERAL CONCEPTS

A disaster can be defined as "a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community's or society's ability to cope using its own resources. Though often caused by nature, disasters can have human origins" (IFRC)

A disaster occurs when people in conditions of vulnerability are affected by a hazard; the impact of the disaster depends on the capacities of the affected communities to reduce the potential negative consequences of the event.
A disaster affects community's life quality, economic activity and social stability. The way the community reacts, influences its future life conditions.

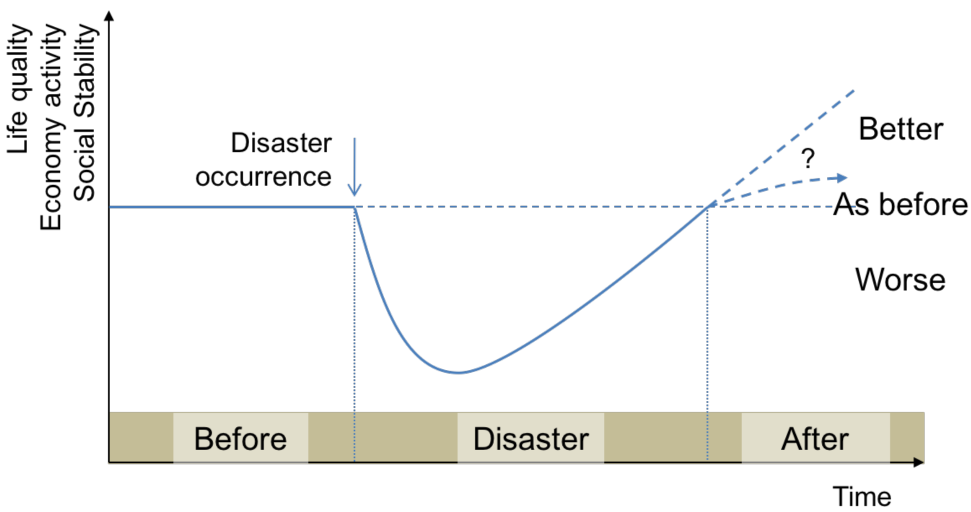

Figure 1 - Influence of a disaster on a society (Adapted from Tobin and Montz, 1997, and Macelino, 2007)

Vulnerability can be thought as the easiness of a person, household or community to be affected by a disaster.
The International Red Cross defines the vulnerability as “the diminished capacity of an individual or group to anticipate, cope with, resist and recover from the impact of a natural or man-made hazard”. The condition of vulnerability depends on physical, economic, social and political factors. For example, the development level of a society its economic condition. Poorer people are often more vulnerable to hazards and due to their lack of capacity, meant as the availability of resources needed to cope a threat or an hazard, are the ones hit in a heavier. In richer countries, or while talking about to Brazil, districts, people have a greater capacity to resist the impact of a hazard. Secured housings and higher incomes increase resilience and enable people to recover more quickly from a hazard.
In order to determine people vulnerability is necessary to understand what threat or hazard are they vulnerable, and what makes them vulnerable (IFRC).

The risk of disaster, meant as the probability of occurrence of a disaster, is a function of the hazard, the vulnerability and the possible effects of the hazard (Tominaga, Santoro, and Amaral 2009).

Disasters can be classified according to the type of originating hazard, natural or anthropogenic (caused by human actions, also known as technological disasters), and rapidness of evolution of the disaster, “slow onset” disasters, “sudden onset” disasters.

	Natural	**Man-made**
Sudden-onset	Earthquake Hurricane Tornadoes	Terrorist Attack Coup d'Etat Chemical leak
Slow-onset	Famine Drought Poverty	Political Crisis Refugee Crisis

Figure 2 - Example of disasters per onset (Van Wassenhove,2006)

A natural disaster take place when a natural phenomenon affects a populated area and causes physical or economic damages. (Tominaga, Santoro, and Amaral 2009).
Natural disasters differ from anthropogenic and technological disaster because they depends mainly on a lack in the society preparedness or capacity to absorb the effects of a natural event, instead of being caused directly by its own action (Albala-Bertrand 2000).

Other relevant characteristics of a disaster are its predictability and its geographic extension, characteristics that strongly influence the logistic operations of response and preparation to the disaster (Apte, Rendon, and Salmeron 2011).

In disaster management can be identified three cyclical phases, preparation to the disaster, disaster occurrence and response, and recovering. Measures for risk mitigation are taken in both the phases of recovering and preparation to a disaster while the occurrence the disaster can be an incentive to the implementation of these preventive measures. (IFRC)

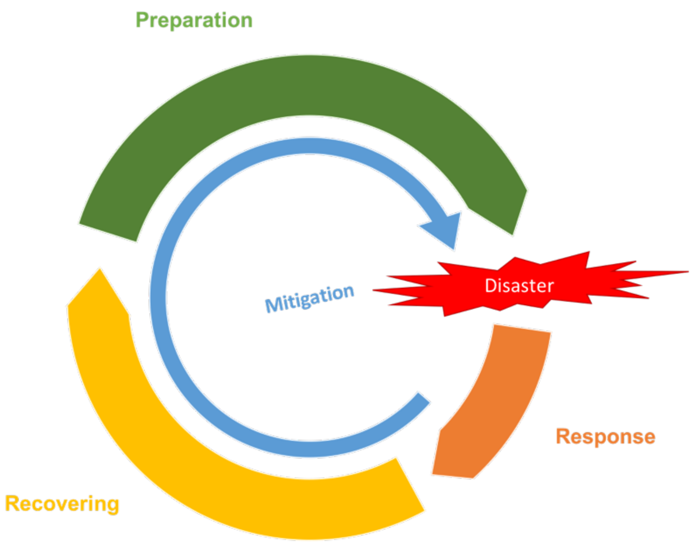

Figure 3 - Cycle of a disaster (Adapted from FEMA,2012 and IFRC,2015)

- Mitigation: set of activities aimed to eliminate or reduce the risk of a disaster or its effect. It can include laws aimed to reduce population vulnerability.

- Preparation: implement mechanisms to face factors the society has not been able to mitigate (Tomasini and Van Wassenhove 2009). In order to respond effectively to a disaster, response strategies have to be planned and recourses have to be made available in advance. Preparing to respond properly can strongly reduce the number of victims and the damages caused by the disaster.
- Response: the act of responding to the emergency. Includes the period immediately after the disaster. During this phase, assistance is provided to affected people and measures aimed to reduce the risk of further damages are taken (Brito Jr 2015).
- Recovering: the affected community try to get back to normality, often with the support of the government. In the short period, essential services and systems are recovered. In the long period the aim is to recover to the previous life conditions or to get them improved (Brito Jr 2015).

Disaster phases can be easily identified in a sudden disaster. In a slow evolving disaster, these phases are not clearly marked and often overlapping. Making the identification of the logistic necessities less clear.

According to the capacity of the community to recover from the disaster and thesuffered damages can be identified four levels of magnitude:

- Level 1: The population capacity can easily absorb the effect of the disasters, damages estimated in less than 5% of the local GDP.
- Level 2: Despite significant damages, the community has the capacity to respond to the disaster and recover from it with a little external intervention or completely without it, damage estimated between 5% and 10% of the local GDP.
- Level 3: The community has not the capacity to face the effects of the disasters, external intervention is needed in order to overcome the disaster, damage estimated between 10% and 30% of the local GDP.
- Level 4: Also defined as catastrophe, the effects of the disaster have a such magnitude that even the most prepared and capable, alone, are not able to face the disaster effects, damages estimated in more than 30% of the local GDP. The most of the normal activities are interrupted, and facilities set in the preparation phase can be affected. Local authorities usually are not able to fulfill their tasks. A rapid and effective

external intervention is critical to respond and recover from the disaster. (Castro et al. 2003; Tominaga, Santoro, and Amaral 2009)

Medias have a great impact on the response phase, mainly by mobilizing volunteers and influencing the quantity of spontaneous donations. Media diffusion however is strongly influenced by economic interest, events with a stronger repercussion and audience has a stronger media diffusion. (Zagefka et al. 2011)

2.1.2. DISASTERS IN BRAZIL AND IN SÃO PAULO STATE

In Brazil, the main natural hazards causing disasters comes from Earth external dynamics, such as inundations and floods, landslides, mudslides, rock-falls and storms. These hazards are usually related to intense and prolonged rains, during rainy season, identified with summer in the South and South-East Region and winter in the North-East Region.

Brazil, according to EM-DAT, is one of the most reached by inundations. From 1960 to 2008, were counted 5720 deaths and more the 15 million people affected. (Tominaga, Santoro, and Amaral 2009)

In Figure 4, a panoramic of the nature of disasters affecting Brazilian territory are listed per Region.

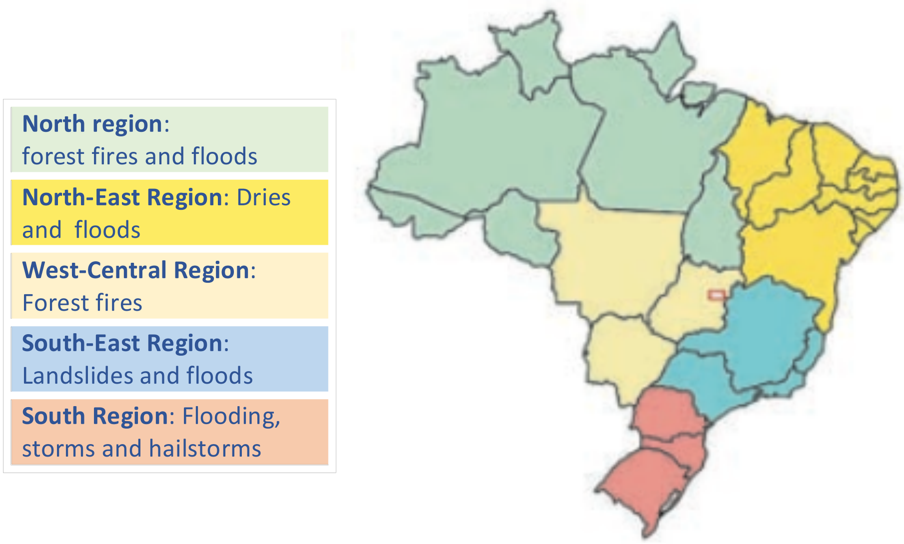

Figure 4 - Disaster distribution in Brazil (Tominaga 2009)

In the São Paulo state natural disaster are associated to landslides, inundations, accelerated erosion and storms. The most part of the State is affected by accelerated erosion (Central and West region, commonly defined in Portuguese as the "Interior" of the São Paulo State), the west region is also affected by soil collapse. In the East region, inundations and sliding are the main hazards. Anyway, floods and inundations are a common phenomenon in the whole state.

A notable recent event is the landslide occurred in the Centro-South region of the Rio de Janeiro State, in 2011, causing 916 deaths and affected directly more than 35 thousand people.

In the São Paulo State, events worth to list are:

- "Vale do Paraiba" in 2010 , an inundation caused 7 deaths ansd affected more the 11 thousand people (Kawasaki et al. 2012)
- recent events occurred in "Itaoca" causing 23 deaths according to Civil Defense data.

Brazil, especially in the last year, his taking into high consideration the question of disaster risk mitigation. Four-year plans are developed in order to implement structural and non-structural measures for reduction of disaster. These measures include improvements in disaster mitigation, preparation and response. Consisting in logistic improvement, risk mapping and monitoring, and vulnerability reduction. (CEDEC)

2.2. LOGISTICS CONCEPTS

2.2.1. INDUSTRIAL SUPPLY CHAIN VS HUMANITARIAN SUPPLY CHAIN

A supply chain can be generally considered as a network involving suppliers, manufacturers, distributors, retailers and customers; and supporting three kind of flows: material flows, information flows, coordinating the material flows, and financial flows. A common element in every supply chain is getting the right goods, at the right place in the right time, distributing them to the right people. (Van Wassenhove 2006)
A representation of a usual industrial supply chain can be seen in Figure 5.

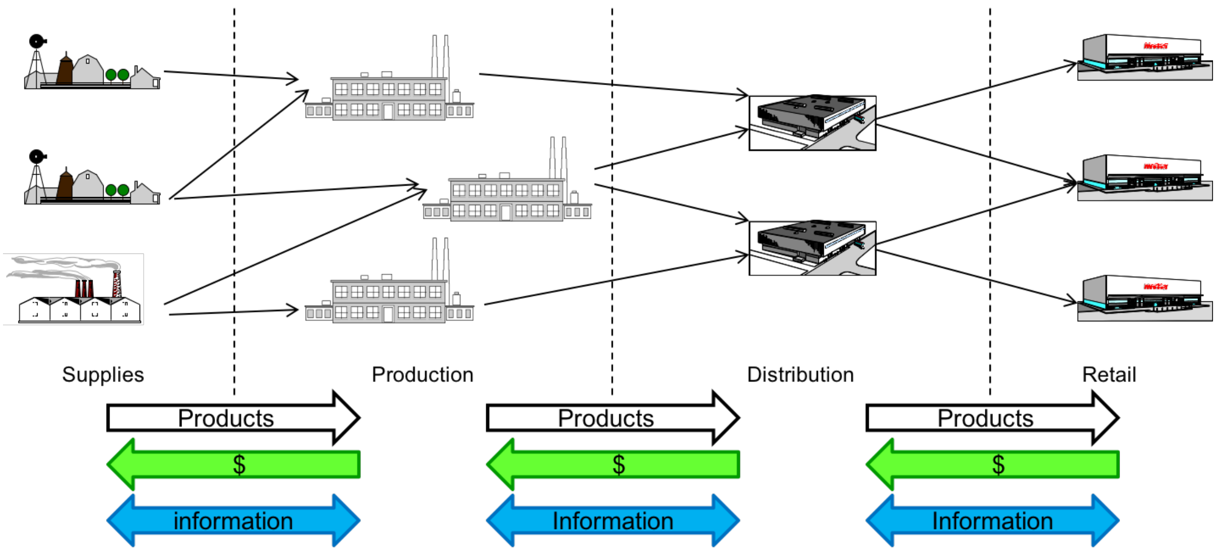

Figure 5 - Industrial supply chain (Adapted from Ballou 2009)

In supply chain management can be identified the following activities: transportation logistics, warehousing, stock management and provisioning.
In industrial supply chain these activities, as well as the demand, are generally a continuous and periodical. The objective of industrial supply chain management is to perform these tasks in the most efficient and cost effective way, in order to maximize the enterprise profits (Ballou 2009).

Humanitarian supply chain management differs from the industrial supply chain management in strategic objectives, demand features, clients and environmental operational factors.
The uncertainty in demand, both in terms of quantity and geographic distribution; its suddenness and the needing to be satisfied satisfy in a short period of time; the lack of resources, technical, human and financial; the operating conditions; together all this factors make humanitarian supply chain management a very complex and challenging field. (Van Wassenhove 2006)
These factors created a very specific supply network, as can be shown in figure

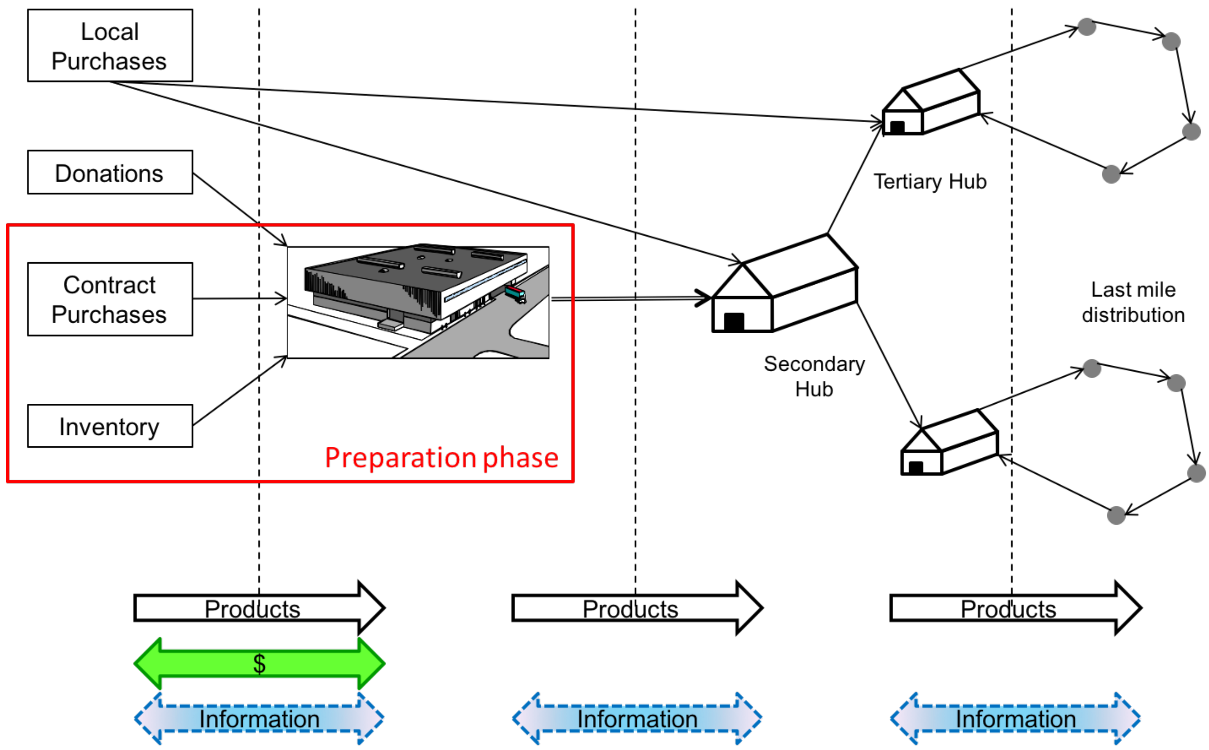

Figure 6 - Humanitarian supply chain structure (Adapted from Ballou 2006, and Blanco and Goentzelel 2006)

In preparation phase supplies are collected in permanent deposits localized in positions of strategic interest. The supplies are acquired through purchase contract with providers or transferred from pre-existing stocks.
In the response phase the relief supplies are delivered to secondary deposits, with a wider capillarity, or directly to the local distribution centers, that deal with the distribution of the supplies to the needy person. These last distribution center can be temporary facilities, set only at the occurrence of the disaster and their localization identified according to the

necessities of the circumstance. During this phase two alternative procurement ways exist, spontaneous donations are made by the population not affected, according to the media divulgation level of the event. Secondary deposits, in case of needing, can realize local purchases. (Nogueira, Gonçalves, and Novaes 2007)
The concept of profit is completely absent. In the first 72 hours after the occurrence of the disaster, the objective is to provide help as fast as possible, independently from the cost of the operation. Later on, up to the 100 days after, cost effective policies are used, the objective becomes a trade-off in being effective in helping people and doing it at a reasonable cost. (Van Wassenhove 2006)
An important feature of a humanitarian supply chain is disaster resiliency. A disaster must impact its operations and efficiency as less as possible.

Humanitarian supply chain management and industrial supply chain management can learn a lot one from the other. Industrial supply chain management could improve its way of dealing with uncertainty, while humanitarian aid supply chain management could learn the idea of continuous improving, subject that often is not taken in sufficient consideration. (Van Wassenhove 2006)

Differently from industrial supply chain, application of mathematical models to humanitarian supply chain get a considerable relevance in academic research only in the last 15 years (Leiras et al. 2014).

2.2.2. LOCATION MODELS

A facility localization model to applicable in this case can be defined as a mathematical model aimed to find the optimal number and locations of deposits, minimizing fixed and variable costs and satisfying a set of constrains.
These resolution methods can be classified according to five criteria:

- Driving force: the most influencing factor for the model. For example, economics in retailing, or service time in emergency response.
- Number of installations: The problem can be about localizing a single, or various facilities.

- Continuum or discrete choice: The localization can be done in a continuous spectrum or only some alternatives have to be analyzed.
- Data aggregation: Often to simplify the model development and resolution, especially when it already involves large sets of parameters and variable, data are aggregated. However, as lower is the data aggregation as higher is the accuracy of the model.
- Time horizon: models can refer to a single period, static models, or to multiples, dynamic model. (Ballou 2009)

A further classification can be done according to the resolution technique:

- Optimizing or exacts: all the alternatives are evaluated, its mathematically demonstrated that the chosen solution is the optimal one. Usually model solved using optimizing technics need large resolution time or computing capacity.
- Heuristic: used to reduce the resolution time, they try to find a satisfactory solution to the problem according to common sense techniques. They represent a tradeoff between solution accuracy and resolution time.
- Simulations: through a mathematical model, representing the main components of a network, the behavior of the system is evaluated according to the various scenarios. Usually the model is stochastic, and various statistical information can be inferred from it.

Objective of the model is not solely the mathematical solution, but also the insight got about the problem structure e behavior and the relations between the model variables. (Geoffrion 1987; Pidd 1999)

2.2.3. LOCATION MODELS IN HUMANITARIAN LOGISTIC

Publications about disaster management teem in social and human sciences, differently than in operational research where a satisfactory number has not been reached yet. In the last years, the trend to treat this field of research is growing, principally due to the increasing number of disaster occurring due to climate changes and global warming. (Altay and Green 2006)

Location model where developed to localize not only relief supplies. Sherali, Carter, and Hobeika (1991) developed a location model for shelters location, using non linear programming.

Current and O'Kelly (1992) elaborated a maximum covering model for nuclear alert sirens.

Srinivasa and Wilhelm (1997) developed a location model for cleaning materials warehouses to use in case of oil leaks, applied in the Galveston Bay, Texas.

Dekle (2005) used a Mixed Integer Programming model to localize center disaster for recovery, imposing that each house should be at the most 20 miles far from the deposit.

Balcik and Beamon (2008), through a maximum covering location model, studied the location of distribution centers for disaster relief supplies and the quantity of supplies to pre-positioned. The objective of the model is to cover the largest possible number of people given a limit response time. Other interesting concepts presented in the work are the estimation of uncertainty, and the connection between the relief supply and the type of disaster.

Viswanath and Peeta (2003) formulated a multiproduct maximum covering model to identify critical infrastructures in case of disaster. The solution, constrained by budget limitation, minimizes the total travel time and maximize the demand meeting.

Ukkusuri and Yushimito (2008) developed model for disaster relief supplies pre-positioning, considering a location problem integrated with vehicle routing. Ruptures in the road network where considered.

Rawls and Turnquist (2010) developed a two stage stochastic model for the location of installations for disaster response, determining also the quantity of supplies to be pre-positioned in each installation. The solution was obtained by means of Lagrangian L-shaped

heuristic given the complexity of the problem. In a further work of published in 2011 service quality criteria where introduced in the model.
In 2012 adapted the model for dynamic pre-allocation of relief supplies, for the meeting of imminent demand. Penalties for unmet demand where considered in the models, also used to calibrate the model parameters. The calibration method, however, is not described in the article.

Salmerón and Apte (2010) used a two stage stochastic model. In the first stage installation location is decided, in the second stage the meeting of the demand is considered. The objective of the model is to minimize the number of deaths. Scenarios with different disaster occurring in different location and with different severity are considered.

Brito Junior (2013) formulated a two stage stochastic MIP model for the location of disaster relief supplies deposits, applied to region of Vale do Paraiba, in the South East of the Brazilian state of São Paulo. The model considered donations, purchases and limitation in warehousing and channel capacity. The model quality has been evaluated through EVPI a VSS.
In a subsequent work Brito Junior (2015) integrated the stochastic model with a MCDA model, in order to take into account qualitative aspects of different consideration in a location model. The integration of stochastic mixed integer programming model and the multi criteria decision analyses lead to more robust tool for the decision making.

2.3. REGRESSION MODELS

2.3.1. MULTIVARIABLE LINEAR REGRESSION MODEL

The objective of a multiple regression is to build a probabilistic model that relates a dependent variable Y to a set of independent variables or predictors. Being X_i the k predictors composing the set, a general additive multiple regression model is expressed by a function

$$Y = \beta_0 + \sum_i \beta_i \cdot X_i \quad i = 1 \dots k$$

The regression error, defied has the difference between the predicted valued and the fitted value is expected to be a random variable distributing according to a normal distribution with mean zero and the expected variance equal to σ^2.
To test hypotheses, calculating confidence and prediction intervals, assumption of normally distributed error is fundamental.
The terms β_i are called regression coefficients. A regression coefficient represents the expected change in the dependent variable Y due to a unit change in the independent variable to it associated.

Predictor variables can be functions of the original independent variables, models containing quadratic predictors and interactions between predictors can still be considered linear. For example

$$Y = \beta_0 + \sum_i \beta_i \cdot X_i + \sum_i \beta_i \cdot X_i^2 \quad i = 1 \dots k$$

Is still linear. Linearity is referred to the coefficients, and not to the variables.

A common method to compute the coefficient of a multi-variable linear regression model is the least squares estimation. The estimated β_i are the result of an overdetermined system of linear equation solved minimizing the sum of the square errorsϵ_i,

SSE is interpreted as the distance between the observed values and the the values estimated by the model.

SST, total sum of squares is a measure of total variation in the observed Y values.

SSR is a measure of the explained variation.

The coefficient of multiple determination R^2:

$$R^2 = 1 - \frac{SSR}{SST}$$

Can be interpreted as the proportion of the observed Y variation that can be explained by the multiple regression model fit to the data, being a common indicator to test the model fitting with the regressed data.

2.3.2. QUALITY CRITERIA FOR MULTIPLE LINEAR REGRESSION MODEL

Differently from simple linear regression, with multivariate data, there is no picture analogous to scatters plot to indicate whether a particular multiple regression model will successfully explain observed y variation. R^2 allows to have a preliminary message about it, but it can be inflated by the large number of variables.

$Adjusted\ R^2$ can be defined as follows:

$$R^2 = 1 - (1 - R^2)\frac{n-k}{n-k-1}$$

Where k is the number of the predictors and n the samples dimension. This value is always smaller to R^2. While the value of R^2 is always included in the interval [0, 1], the value of $Adjusted\ R^2$ belongs to the range 0, R^2. $Adjusted\ R^2$ can be a useful tool while choosing the number of independent variables to include in the model.

A formal test for the model utility is needed.

The model utility test in simple linear regression consist in rejecting the null hypothesis $H_0: \beta_1 = 0$, according to which there is no useful relationship between Y and the single predictor X.

The assertion to be considered in this case is that all the regression coefficients are null, that means that there no useful relationship between the independent variable Y and any of the dependent variables X_i;
Another tool to assess the model adequacy is the standardized residuals normal probability plot, as already told, the normality of the residuals is the base for the reliability of the estimations of confidence and prediction intervals and all the statistical tests. The normality of the residuals is highly recommended, but it is proved that a model can still be reliable even if the residuals are not normally distributed, provided that the number samples is large enough, the lower threshold for the sample dimension has been estimated to 15 elements. (Lumley et al. 2002)

In defining a multiple regression model is fundamental the choice of the predictors. Diffused criteria are:

- Maximization of the Adjusted R^2
- Minimization of the MSE
- F-test for the single variable

The best way to choose the independent variables to include in the model is to evaluate all the possible combination of variables according to the chosen criteria. This method is not always possible depending on the number of available independent variables. In order overcome this problem Iterative methods, defined as stepwise method have been implemented.
Starting from a given set of predictors, these methods check the model reving the set of included variables, or functions of them, at each step, trying to improve the model according to the chosen criteria:

- FS, forward selection: at each step a variable is added
- BS, backward selection: at each step a variable is removed
- FB, a mixture of the previous methods according to which, firstly, predictors proving the model are added; in a second phase the one badly influencing the model are removed. (Devore, Farnum, and Doi 2013)

As important as choosing the right variables is understanding if in the models there are samples influencing the model in much heavier way than the others. Two important diffused indicators identifying these values are the Leverage and the Cook's Distance.

The Leverage of the observation i is the i-th diagonal term of the hat matrix. An observation i can be considered an outlier if its leverage substantially exceed p/n.
Cook's Distance is the scaled change in fitted values, defined as the normalized normalized change in the vector of coefficients due to the deletion of an observation.
A value of Cook's Distance higher than 4/n indicate a highly influential value (BOLLEN, 1990).

2.3.3. GENERALIZED LINEAR MODELS

2.3.3.1. Overview on GLMs

Often common linear models are not sufficient to describe the behaviors of a dependent variable. In these cases, generalized linear models can be the solution.

A generalized linear model, or generalized additive model, removes the constraint of the dependent variable to be normally distributed.

A general linear model is characterize by two feature:

- The nature of the variable, discrete or continuous, and its probability distribution
- The relation between the dependent variable and the predictor ones

This implies that, to develop generalized linear regression model the distribution of the dependent variable should be known.

A generalized linear model present the following formula:

$$g(E(Y)) = \beta_0 + \sum_i \beta_i X_i$$

The function g is called the link function and is a simple mathematical function. In theory, the estimation is straightforward. In practice, it may require a considerable amount of computation involving numerical optimization of non-linear functions.

The estimation is done using Maximum Likehood Estimation methods. These methods, once defined a function measuring the fit of the model with the data in input, generate a model for which the value of this function is maximized.

Generalized linear model can be applied in all the cases in which the dependent variable presents a distribution belonging to the exponential family. The link function depends on this distribution. (Dobson 2002)

In generalized regression model fitting quality cannot be always evaluated according to the standard criteria. Using quantile-quantile plots to the test negative binomials or logistic generalized linear models for example can be dangerous and lead to erroneous evaluations. (Ben and Yohai 2004)

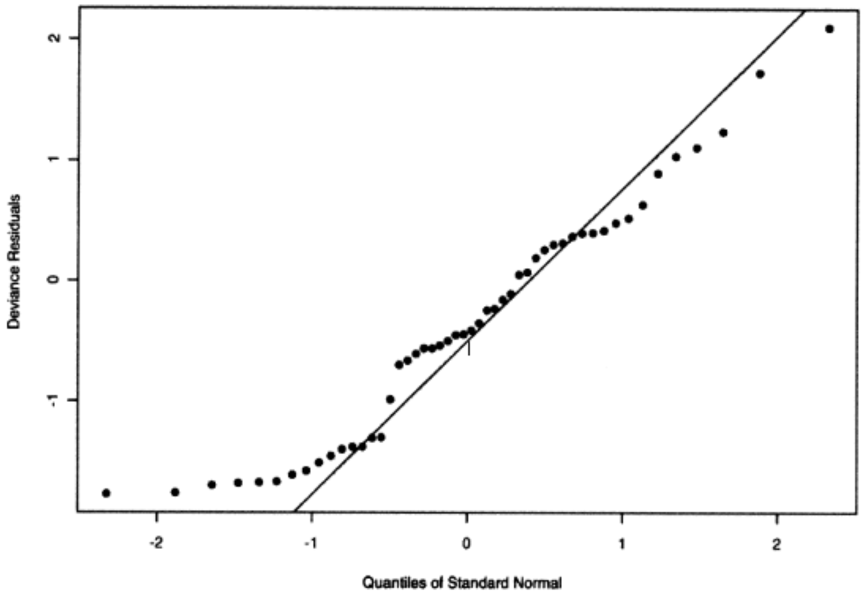

Figure 7 - Normal Q-Q plot of the deviance residuals for the artificially generated negative binomial regression example of sample size 50 (Ben and Yohai 2004).

In Figure 7 can be seen that the Q-Q plot present a shape that according to criteria for linear models would mean a bad fitting, absolutely not true in this case, given that the data have been artificially generated.

2.3.3.2. Zero-inflated generalized linear models

In the case in which depending variables in a count variable with data presenting over dispersion, or an high number of zero values, zero-inflation, zero-inflated models should be used.

A zero-inflated GLM treats the zeros present in the depending variable as a different variable, estimating them with a dedicated regression model.

A zero-inflated regression model is composed by: a count model, usually a generalized linear model for Poisson or negative binomial distributed depending variables and a binary model, usually a logistic regression model that deals with the zeros of the depending variable.

2.3.3.3. Comparing generalized linear models

Comparisons of best fitting for different models given a certain dataset has to be done differentiating two cases:

- The models are nested, that means that a model can be obtained adding an independent variable to the other or changing its parameters, it is the case of generalized linear model for Poisson distributed depending variables and generalized linear models.
- The models are not nested, what said preciously is not possible. Comparison between zero-inflated and not zero-inflated models.

In the first case, F-test of model statistical significance, or coefficients statistical significance can be used.

In the second case, the use of a special test, Vuong Test, is needed. Vuong test compares two non-nested models showing which of the two has a best fit with the data. The test furnish starts from the assumption the two models fit equally well the data and gives the p-value of the best model fit being better of the other one. (Vuong 1989)

Vuong test is implemented in R in the function *vuong*, of the package *pslc*.

3. DIAGNOSTIC AND PROBLEM DESCRIPTION

3.1. SÃO PAULO STATE

With 645 municipalities, about 44 million estimated inhabitants, the State of São Paulo is the most populated State of Brazil, and the third more populated political unit of South America, surpassed only by the Brazil itself and Colombia.

It has an area of 248 222.6 km^2, comparable with the UK area, that makes it the 12th largest of the 27 Brazilian State.

São Paulo City, the State Capital, considering its metropolitan area reach 20 935 204 inhabitants, being the largest city of South America and ranked 13th in the world largest cities.

If we include into its metropolitan area the regions near the capital (Campinas, Santos, Sorocaba and São José dos Campos, Santo André, São Bernardo do Campo, São Caetano, Diadema, Piracicaba, Guarulhos, Osasco) it exceeds 31 million inhabitants, approximately the 75% of the whole state population. This conurbation, representing one of the most populous urban agglomerations in the world, is called the “Expanded Metropolitan Complex”.

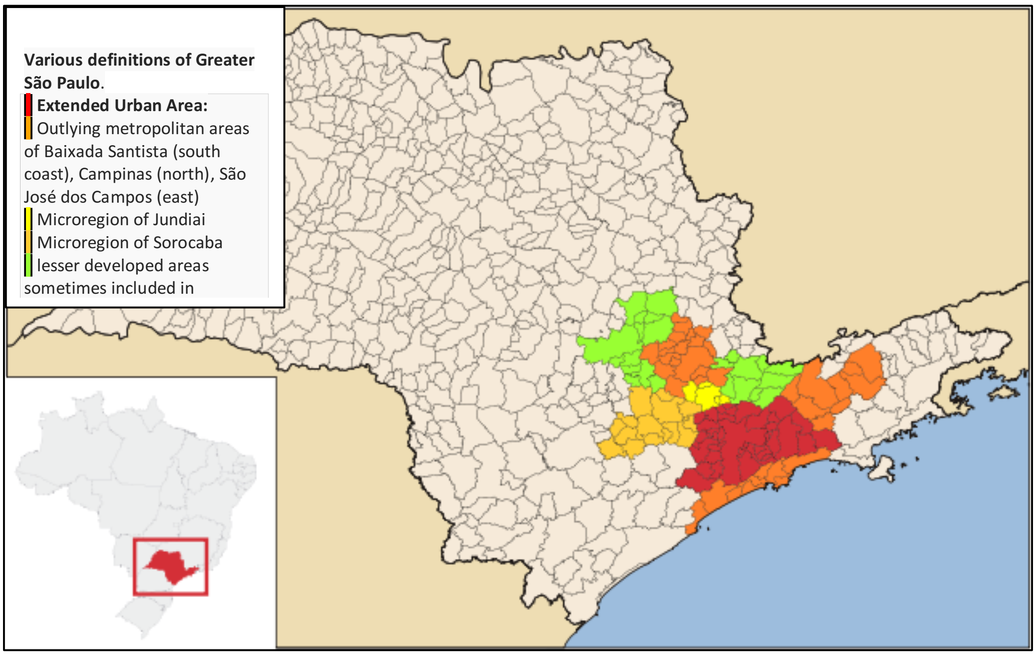

Figure 8- Definitons of Greater São Paulo (Wikipedia, 2015)

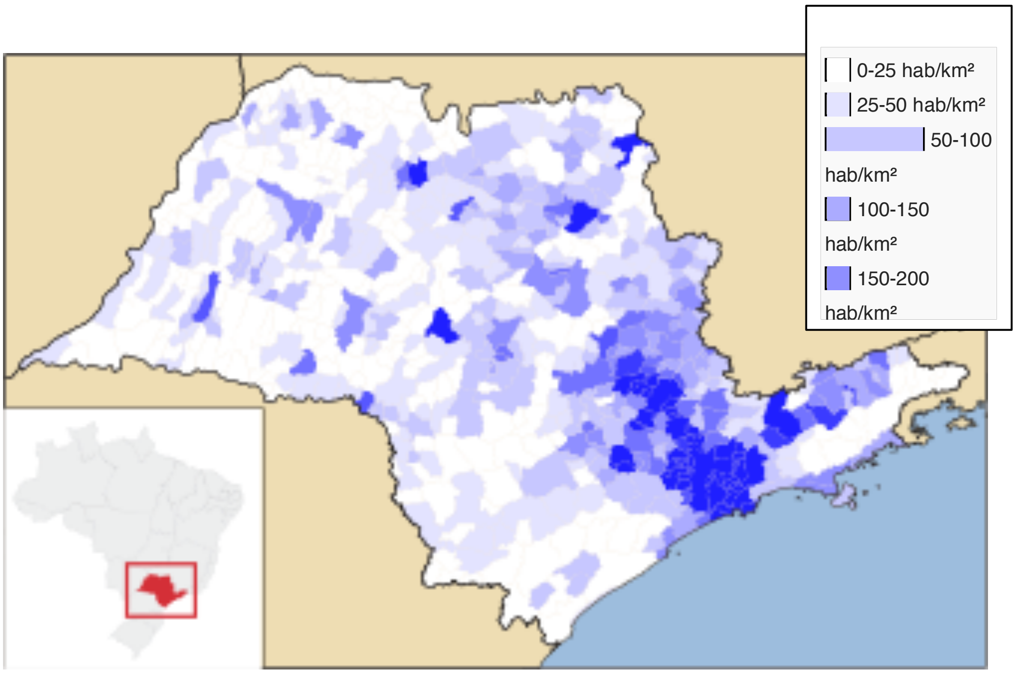

Figure 9 - Density per city of the São Paulo state (Wikipedia, 2015)

São Paulo State is often dubbed as the 'locomotive of Brazil' being responsible for about a third of the whole Brazilian GDP. The State's GDP consists in 909.05 billion dollars (IBGE data, 2014), making it the biggest economy of South America. The main industries are metal-mechanics, sugarcane, textile and car and aviation manufacturing. Service and financial sectors, as well as oranges, cane sugar and coffee cultivations play an important role.
The wealth is strongly unequally distributed in the State, however. The richest municipalities clusters around the Greater São Paulo.

The main transportation mode is road transport, the São Paulo State presents the largest statewide road transportations system in Brazil. With 34 650 km of road, the highway system consists of a hugely interconnected system network of municipal (11 600 km), state (22 000 km) and federal (1 050 km) roads. More than 90% of the population is within 5 km of a paved road.
Railways are quite inexistent statewide, the few existing ones are concentrated in the Greater São Paulo, or are dedicated to freight.

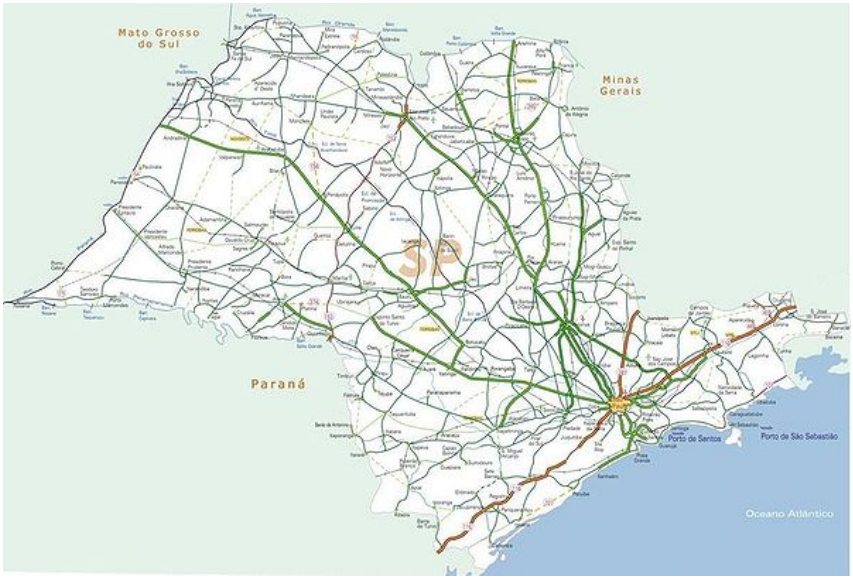

Figure 10 - Highway system of the São Paulo state (Wikipedia, 2015)

São Paulo state is located in the South-East Brazilian Region, the climate is tropical to subtropical, being altitude the most influencing factor. The rainy season coincide with the Brazilian summer period. The territory is mostly hilly (85%).
It is inserted in three hydrographic regions, which the most important is the “Parana Basin”. Presenting a high density of rivers, often navigable, and lakes.

Due to the tropical climate, the heavy rainy season, and the strong presence of rivers and the hilly territory, São Paulo state is highly affected by natural hazards. Landslides, mudslides, floods, accelerated erosion and windstorms are daily events. In Figure 11 can be seen the more common event per area.

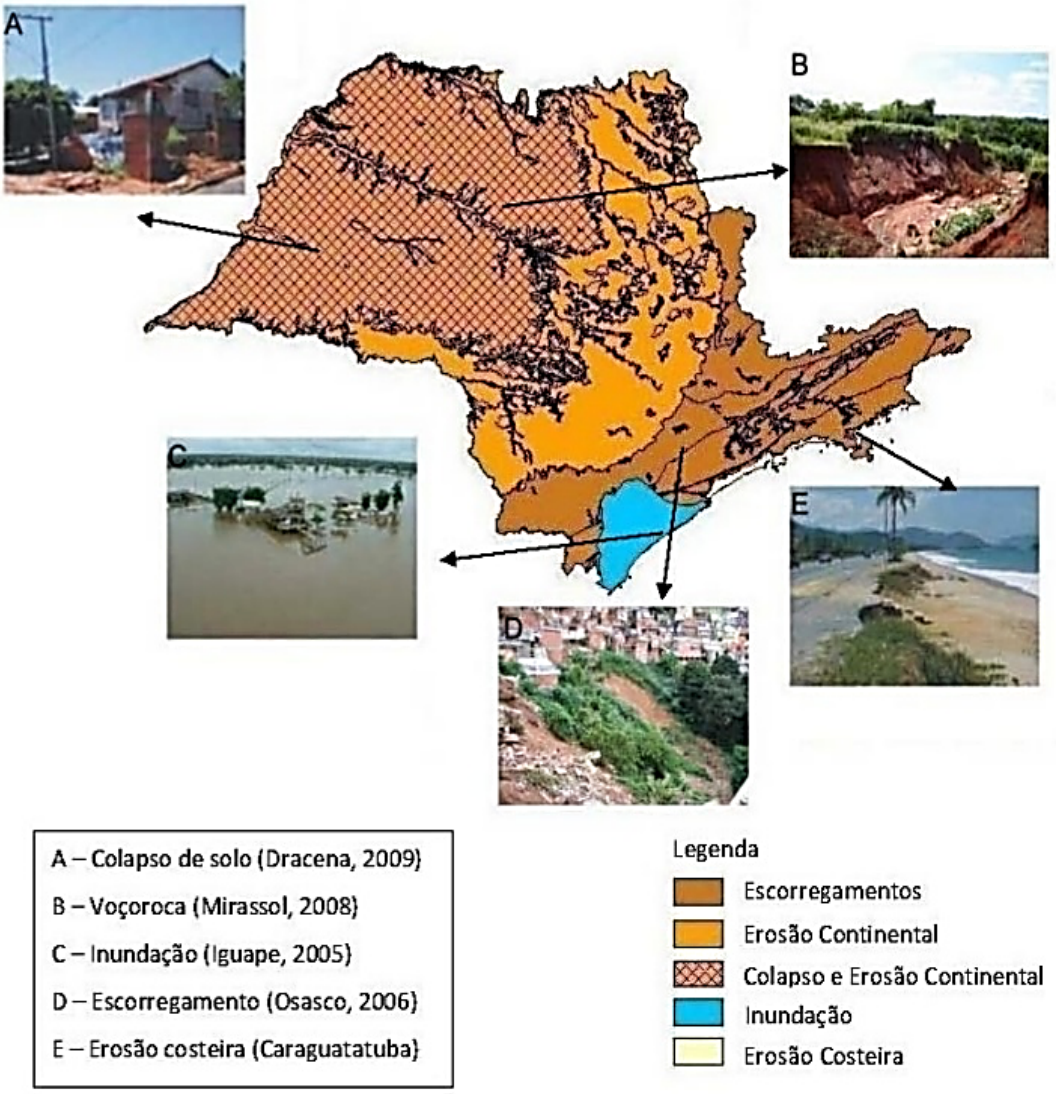

Figure 11 - Disaster distribution in São Paulo state (IG,2008)

3.2. SÃO PAULO STATE CIVIL DEFENSE

Is the national institution for the protection of the society during abnormality situations, acting by means of actions of prevention, mitigation, preparing and response.

Its duty is to coordinate and supervise civil defense actions, to maintain and update specific information, elaborate and implement projects and programs, estimate budget for humanitarian actions, train human resources, manage assistance supply chain and evaluate the emergence level of the disaster.

Each Brazilian State organizes its Civil Defense body independently, following the national guidelines given by the "National Policy of Civil Defense". The direction of the system is up the State Governor, by means of the State Coordinating body of Civil Defense ("Coordinadoria Estadual de Defesa Civil, CEDEC"), under the leadership of the Head Secretary of the Military House of the Governor Office ("Secretario-Chefe da Casa Militar do Gabinete do Governador").

CEDEC integrates member from various other civil and military offices.
It branches into the territory trough 19 Regional Coordinating bodies ("Coordenadorias Regionais de Defesa Civil, REDEC"), each one supporting the Municipal Coordinating bodies ("Coordenadorias Municipais de Defesa Civil, COMDEC") belonging to the pertinence region. Often, especially in smallest and poorest cities, COMDECs do not have its own facility, but simply consists in a group of people trained to respond to the disaster, often they are volunteers.

REDECs heads must not compulsorily belong to Civil Defense Body, they can be part of the fire department ("Corpo dos Bombeiros"), the military police ("Policia Militar") or be at the direct dependencies of the Environment Secretary of State. REDECs head change periodically, according to Government decisions.

REDECs split in Metropolitan ones, referring to the São Paulo city metropolitan area, and “interior” ones, referring to the rest of the state, a complete list of the cities belonging to each REDEC can be found in Appendix 1.

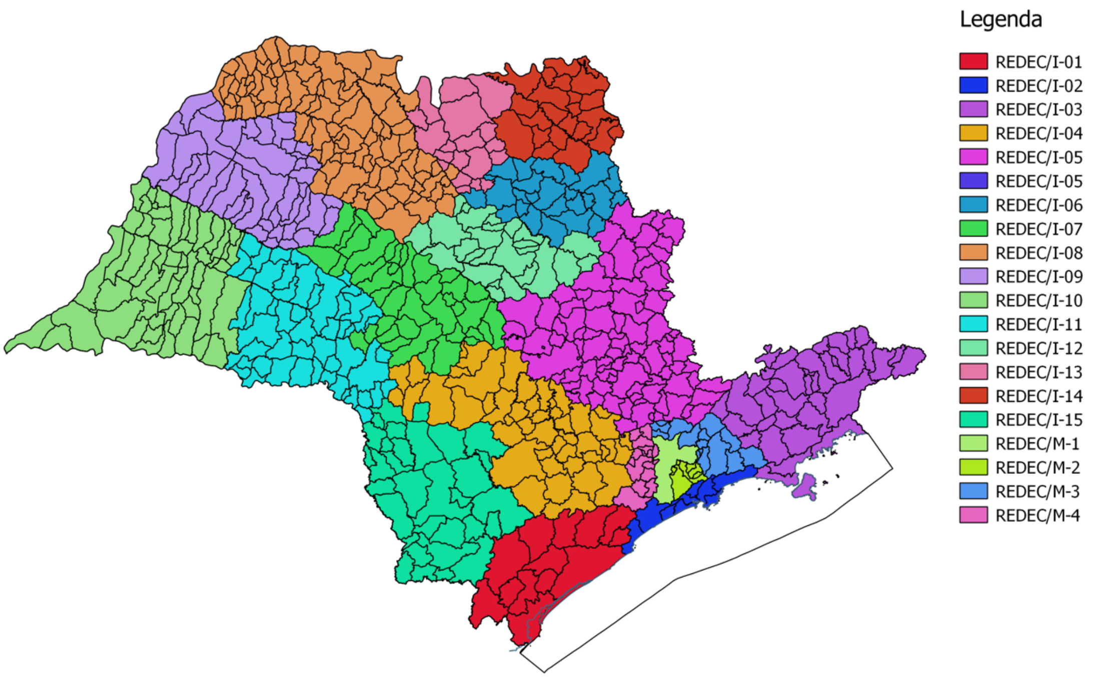

Figure 12 - Civil Defense REDECs

The actual CEDEC-SP logistic network counts a central warehouse located in the city of São Paulo, and other seven secondary warehouses in the “Interior”, in the cities of Apiaí, Aracatuba, Bauru, Caçapava, Presidente Prudente, Registo and Ribeirão Preto. Each warehouse is in charge of attending the nearest city depending on the availability of relief materials.

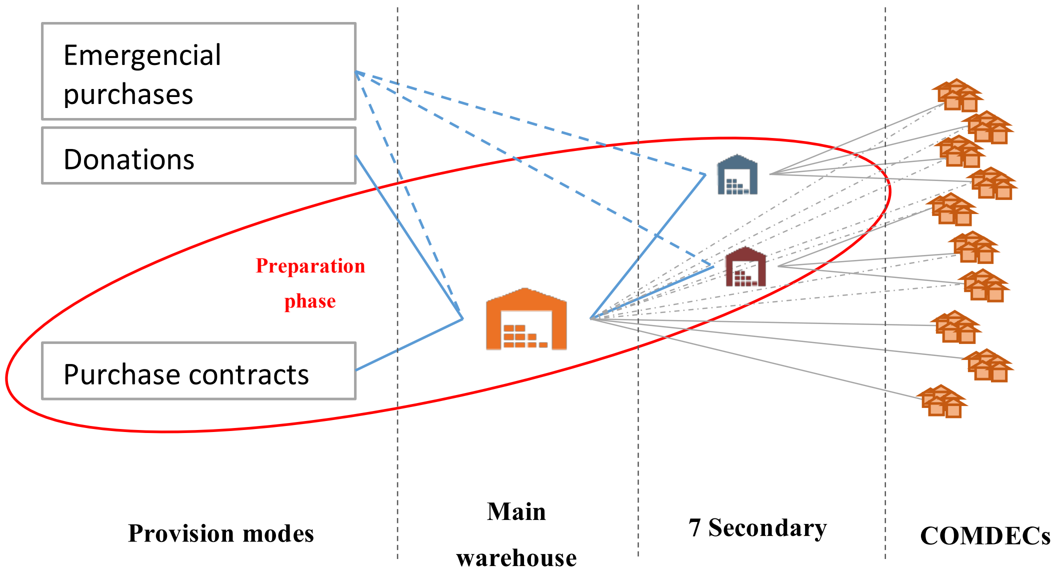

Figure 13 - São Paulo State Civil Defense logistic network structure

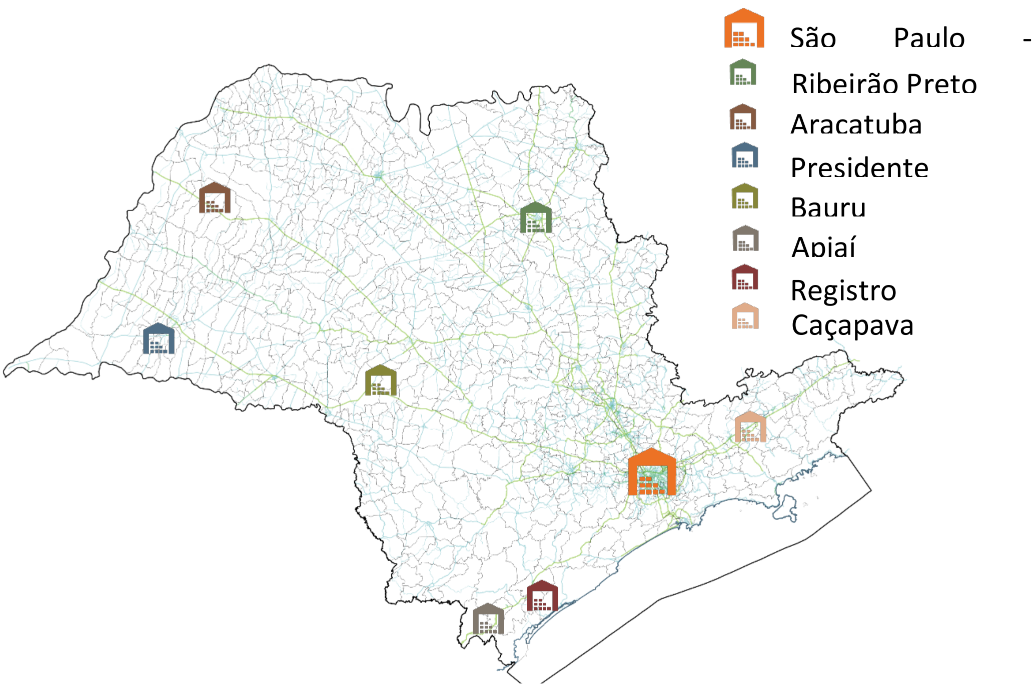

Figure 14 - Civil Defense warehouses distribution (REDEC,2015)

The central warehouse is located in the Morumbí district of the city of São Paulo, in a position allowing a fast access to the highways system.

It has stocking area of approximately 50x10 meters, and is operated by 3 employees.

Figure 15 - São Paulo Morumbí central warehouse (REDEC,2011)

The secondary ones have a much smaller dimension, and capacity. They are set up in existing facilities, often, without the proper features a warehouse should have.

While the choice of the city in which the secondary deposits have to be localized is done centrally. Their location in the city is done by the REDEC responsible for the city, according to criteria of space availability and capacity of the actual Head to keep the warehouse under surveillance. Security is a factor to be taken into high consideration. This implies that with the same periodicity the REDEC Head changes, the warehouse localization can change.

The stored items can be divided in two categories, support items directed to the COMDECs, consisting in safety equipment and tools for COMDEC's personnel and volunteers, and relief items directed to the population affected by the disaster.
Relief items can be grouped in the following kit according to their function:

- Basic Food Basket: shipped per affected family, contains food to feed 4 people for a period of 15 days;

Figure 16 - Basic food basket stocked in the central warehouses (REDEC,2011)

Figure 17 - Basic food basket and part of thre Cleaning Kit stocked in the central warehouse (REDEC, 2011)

- Hygiene Kit: shipped per affected family, contains the basic hygiene tools for a family composed by four people.
- Bedding Kit: shipped per affected person, contains the complete set of mattress and beddings.

Figure 18 - Beddings stocked in the central warehouse (REDEC,2011)

- Dressing Kit: shipped per affected person, contains a shirt, a sweater and a pair of tennis shoes.
- Cleaning Kit: shipped per affected family, contains all the tools needed to clean a place after the event.

Figure 19 - Parts of the cleaning kit stocked in the central warehouse (REDEC,2011)

Figure 20 - Brooms and beddings stocked in the central warehouse (REDEC,2011)

In addition to support tools and safety equipment, COMDEC's materials count also plastic canvas and measure instruments (i.e. pluviometers). Except for the plastic sheets, which shipped number depends on the magnitude of the disaster, these material are shipped according to request done from the COMDECs according to their needing.

A complete list of the materials can be found in Appendix 2, together with all the information about each supply material.

Materials are stocked in separate rooms, minimizing the contact between hygiene and cleaning products with food and dressings.
No other particular attentions are given to the stocked material, exception done for basic food basket, due to bean bags short expiration time, they have a validity of 3 months, replacing these bean bags basket, validity can be doubled. In order to minimize the waste of food, 40 days before the expiration date the unshipped baskets are given to humanitarian institutions, dealing with poorer communities, as the "Fundo Social do Estado de São Paulo" (FUSSESP).

3.3. THE PROPOSED WAREHOUSE

According to CEDEC the new warehouses will consist in a thermo-resisting PVC canvas warehouse, with an estimated lifetime of 10 years. Their dimensions are: 20 meter long, 10 wide and 5 high.

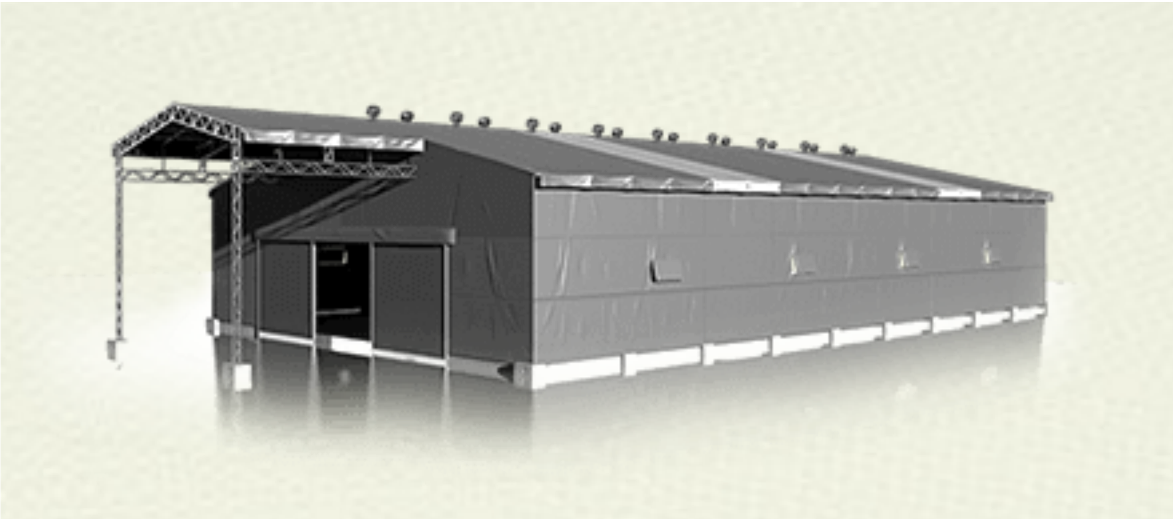

Figure 21 - Example of Canvas warehouse (Sansuy,2015)

The deposits could theoretically be located in each city presenting a fire department or military police station. For sake of calculation time economy only cities with a population larger than 25 thousand have been taken in consideration as a possible location. Most part of the metropolitan REDECS cities, consisting of the cities of the Great São Paulo, have been excludes from the possible candidates, because of their proximity with the central deposit. A list of the candidate locations can be found in Appendix 3.

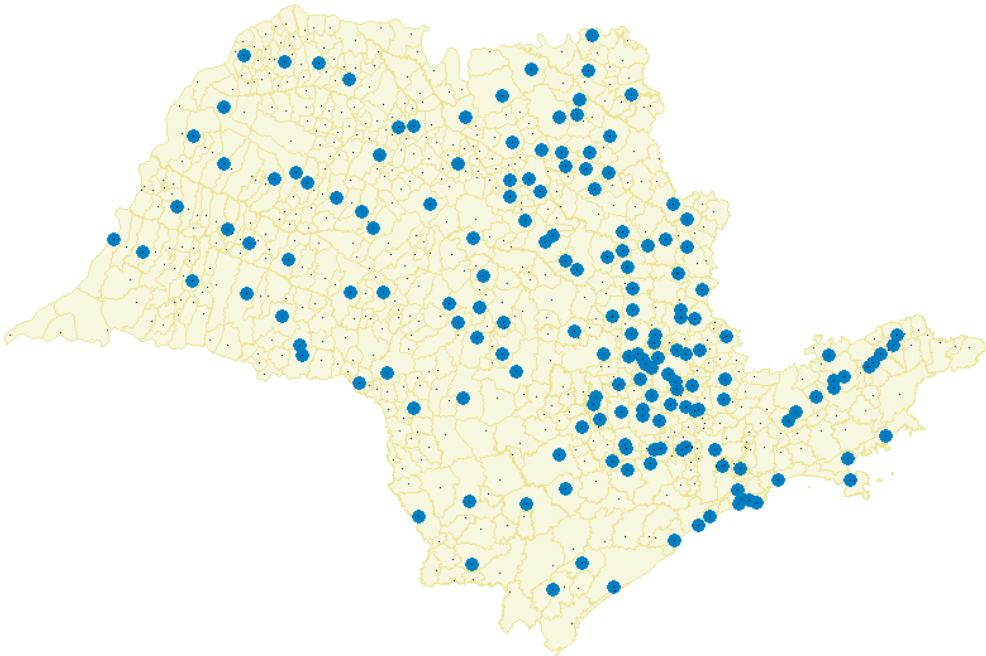

Figure 22 - Candidate warehouse locations (Adapted from IBGE,2010 and CEDEC,2015)

3.4. AVAILABLE DATA

3.4.1. HISTORIC OF INTERVENTIONS

Starting from 2001, CEDEC-SP started keeping a structured historic database of its interventions, during “Summer Operation”, listing the number of victims of the event, the people forced to leave their own houses and the nature of the intervention.

Anyway, this structure kept changing in the first years. Starting from 2006 the final data collection and reporting standard has been implemented.

The historical series are collected per year and REDECS, and the following information are listed: city of the interventions, district or street, what caused the interventions, injured people, missing persons, deaths, evacuees with alternative housing, homeless evacuees and the nature of the hazard, lightings, floods, landslides, storm, soil collapse.

Unfortunately, data about district and nature of the interventions has not been standardized yet, making impossible to work these data with ease.

To analyze the data, they need to be aggregated in order to obtain a database including all the interventions.

The complete database counts 3302 interventions in 365 cities from 2001 to 2015.

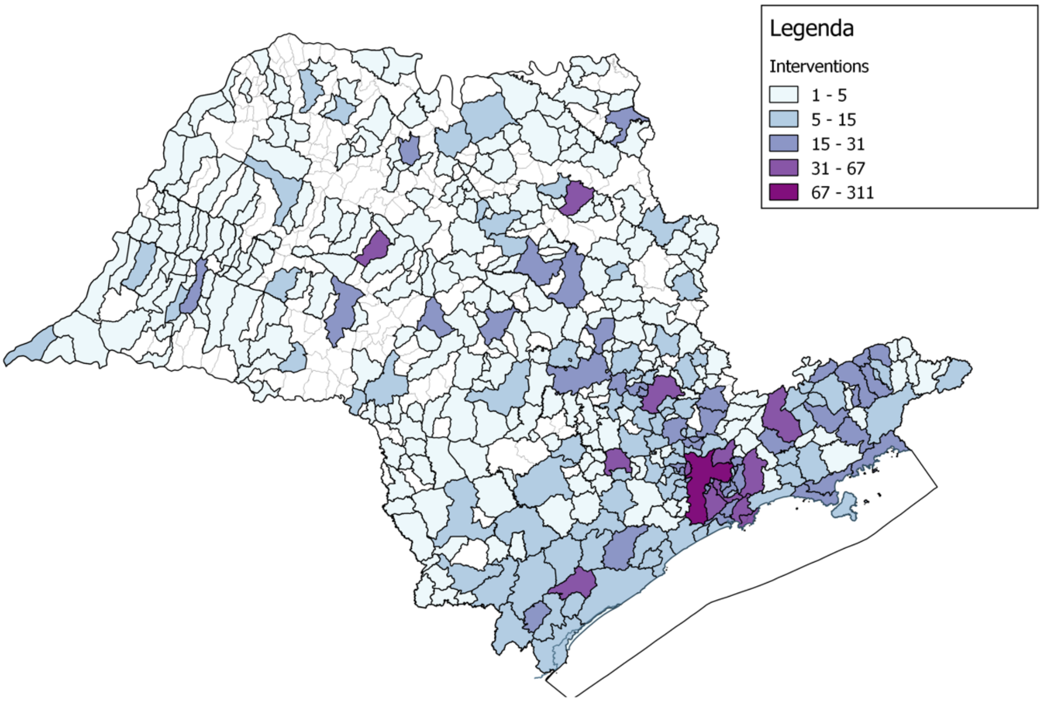

Figure 23 - Civil defense interventions per city

The interventions concentrate in the south and south-east region of the state, areas with an high risk of floods and landslides. The cities with the highest number of intervention are also the most populated ones. From the map represented in Figure 23 can be inferred that Capital, São Paulo, presents the highest number of interventions. The whole metropolitan area present and high number of interventions.

It can be noticed that the south region, known as "Vale do Ribeira", even if not densly populated presents a high number of interventions.

Considering the number of intervention per 1000 city inhabitants, it is possible to put on evidence some area that even if poorly populated needed a high number of interventions. The extreme south region, "Vale do Ribeira", the extreme east region, "Vale do Paraiba" and estreme west region, that we will identify with the region of "Presidente Prudente", fall into this category.

It is worth to list the cities of São Luiz do Paraitinga and Canas that presented the highest number of interventions per 1000 inhabitants.

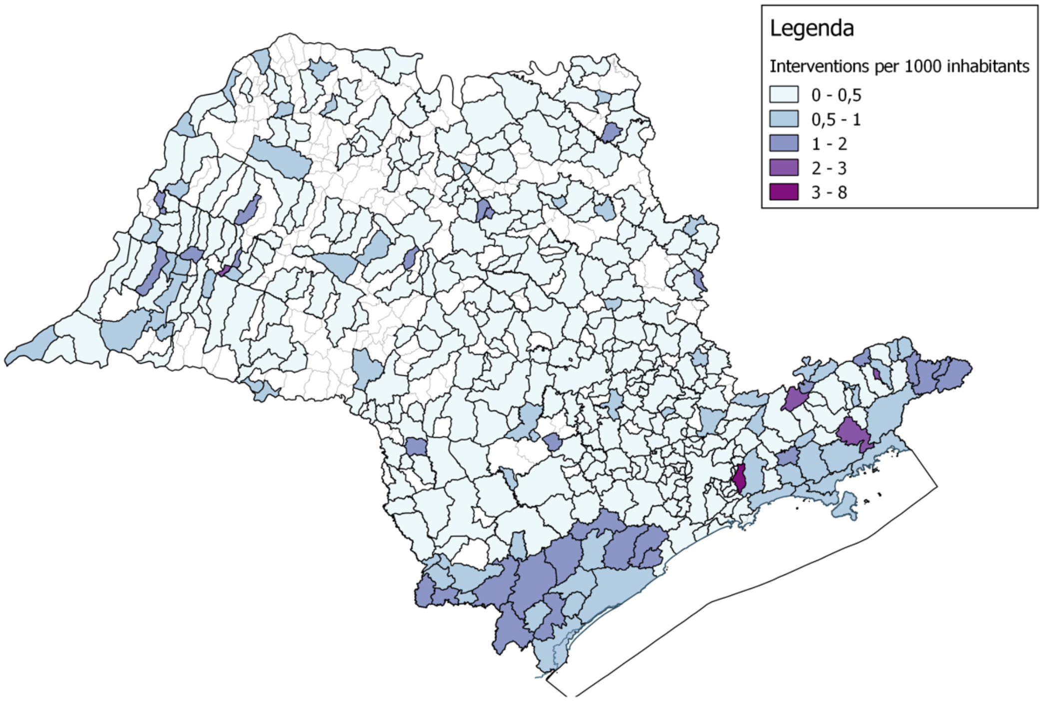

Figure 24 - Civil Defense interventions per 1000 inhabitants

If we consider the number of affected people during the natural disaster, causing the intervention, the situation is pretty similar, the number of affected people is generally higher in the most densely populated cities. Again the the region of "Vale do Paraiba" and "Vale do Ribeira", present relatively higher statistics with respect to the rest of the state.

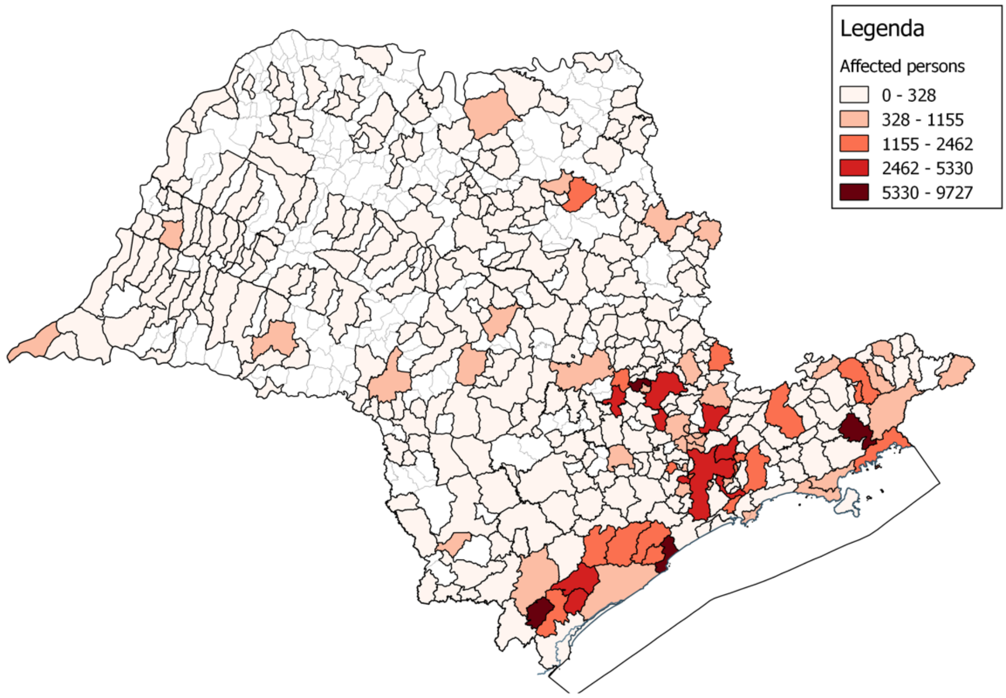

Figure 25 - People directly affected by disasters

3.4.2. RISK PREPARATORY PLANS

Due to high frequency of natural disaster, and thanks to federal and state policies municipal preparatory plans for risk evaluation have been and continue being developed. These plans contain a mapping of the areas at risk, reporting the type of hazard the area is at risk to and the level of risk.
According to the life risk of the people living in the area, can be identified four levels of risk:

- R1: low risk
- R2: medium risk
- R3: high risk
- R4: very high risk

It is assumed that independently from the type of hazard, and the place of occurrence of the event people at a certain risk level have the same probability to be affected by the disaster.

These estimation of risk have been done statewide by a series of Brazilian geology institution, here listed the principal one

- CBH-RB: Committee of Hydrographic Basins of the "Ribeira de Iguape" and South Littoral.
- CPRM: "Companhia de Pesquisa de Recusos Minerais", also know Geological service of Brazil
- IPT: "Istituto de Pesquisa Tecnologica", in English Institute of Technological Research
- IG: Geosciences Institute of the University of São Paulo

Other institution are the municipalities themselves, or private consultants. The four listed institute, anyway, are responsible for 361 of the 381 risk reports redacted (about 95%), for 245 cities. Some cities updated their preparatory plans several times.
Each institution, also depending on the year of redaction of the report, followed a different reporting structure. Usually the data about the number of houses at risk is aggregated for district, a total is not expressed.

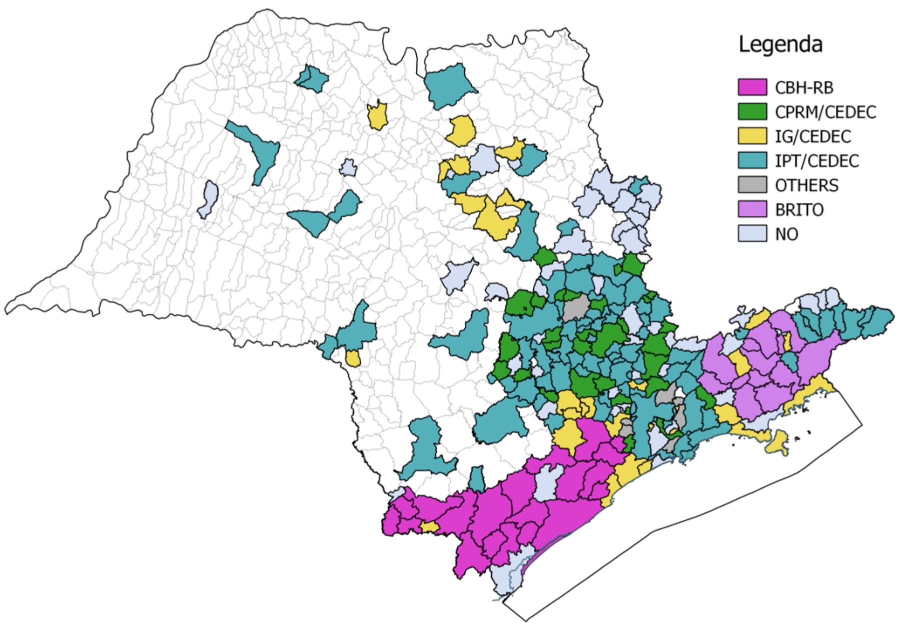

Figure 26 - Sources for the number of people living in risk condition

Considering only the latest risk reports versions, only from 195 is possible to extrapolate the number of houses at risk, (a good estimation of people at risk can be done by multiplying the average number of residents per house, IBGE 2010 data, per city for the number of houses at risk).

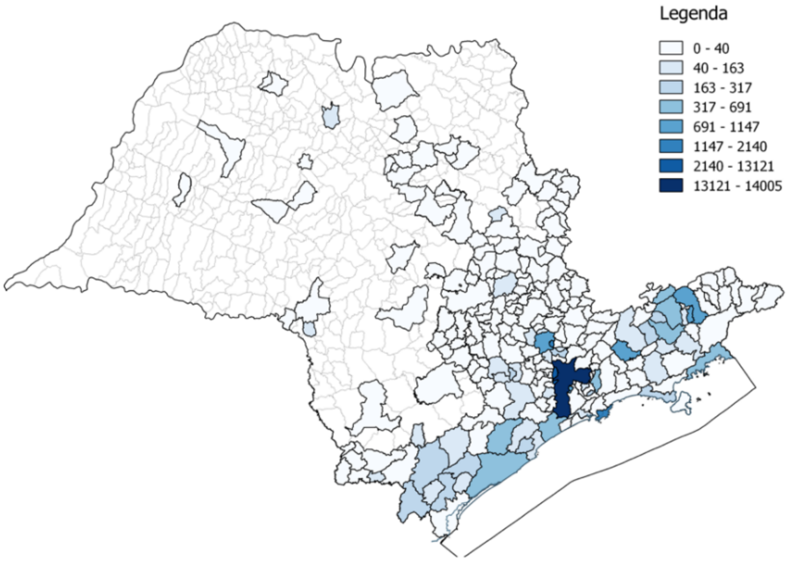

Figure 27 - People living in risk condition R1

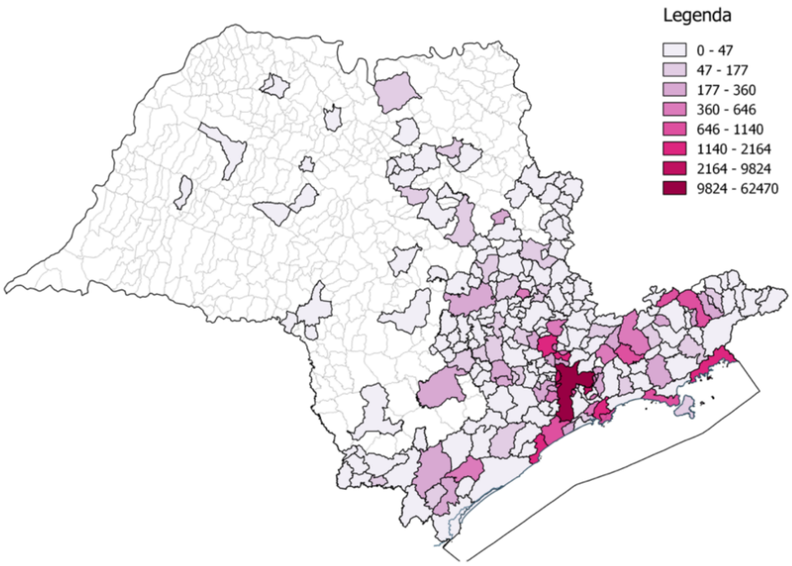

Figure 28 - People living in risk condition R2

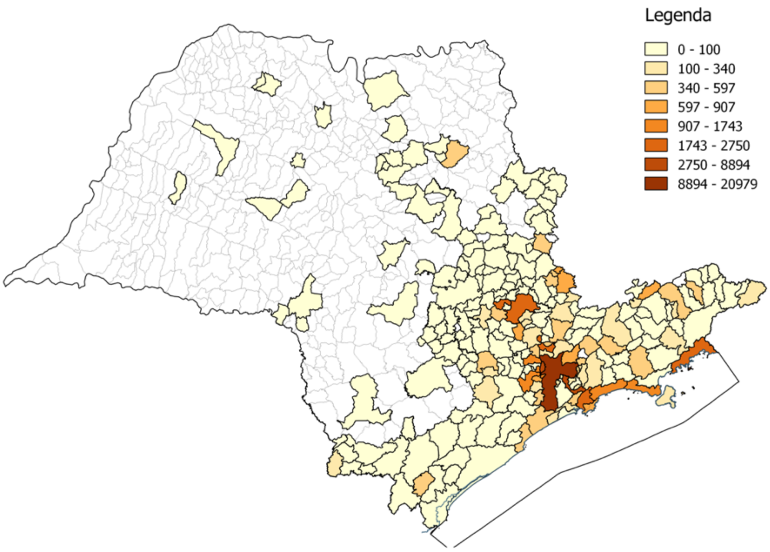

Figure 29 - People living in risk condition R3

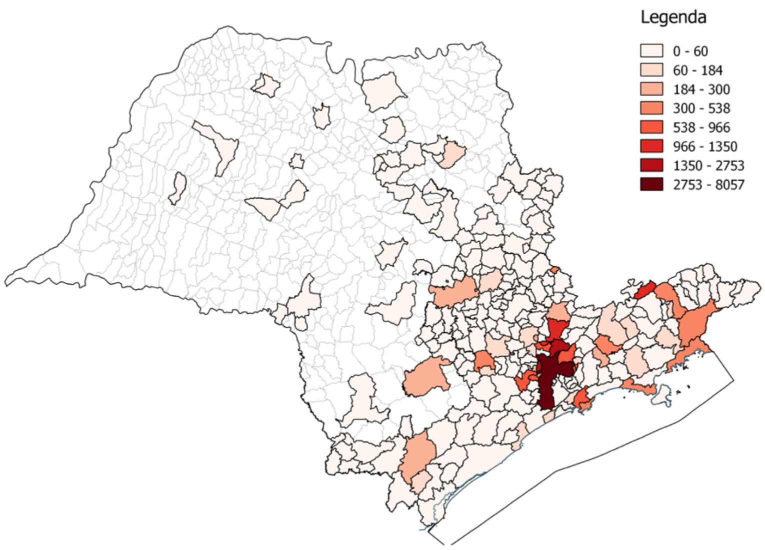

Figure 30 - People living in risk condition R4

The same behavior noticed for the affected people and the number of intervention happens for the number of people at risk for each city. The quantity of people living in a risk condition increase with the increasing of city inhabitants.

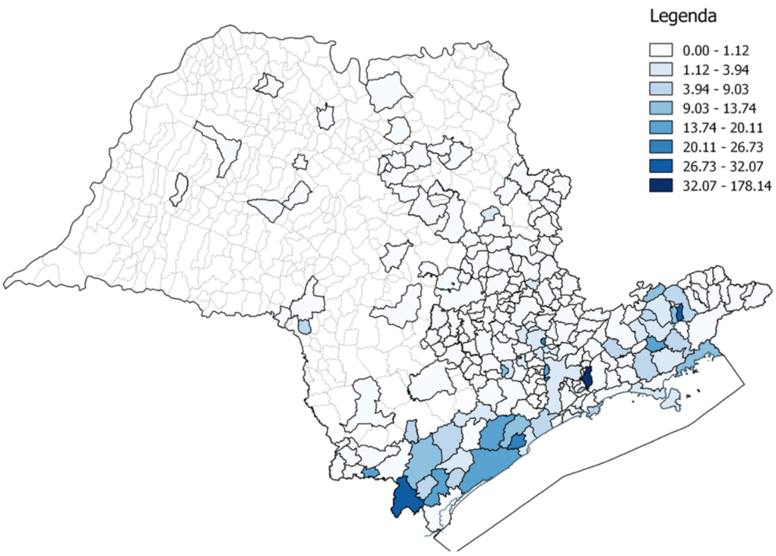

Figure 31 - People living in risk condition R1 per 1000 inhabitants

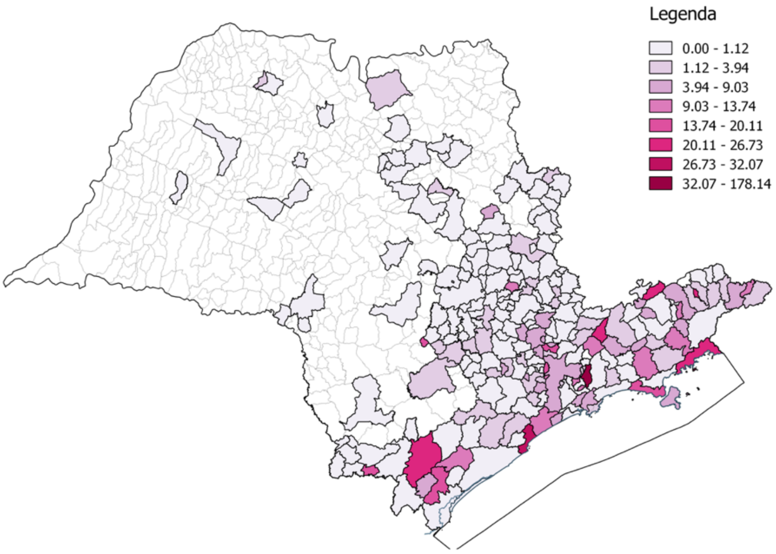

Figure 32 - People living in risk condition R2 per 1000 inhabitants

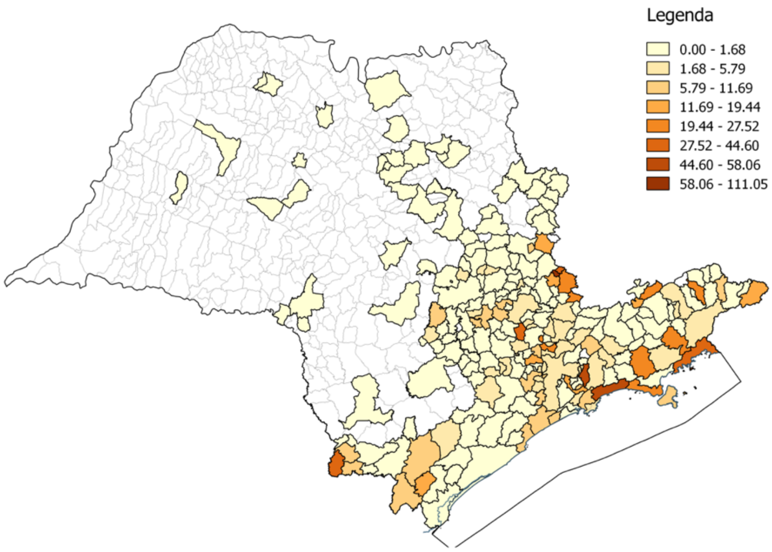

Figure 33 - People living in risk condition R3 per 1000 inhabitants

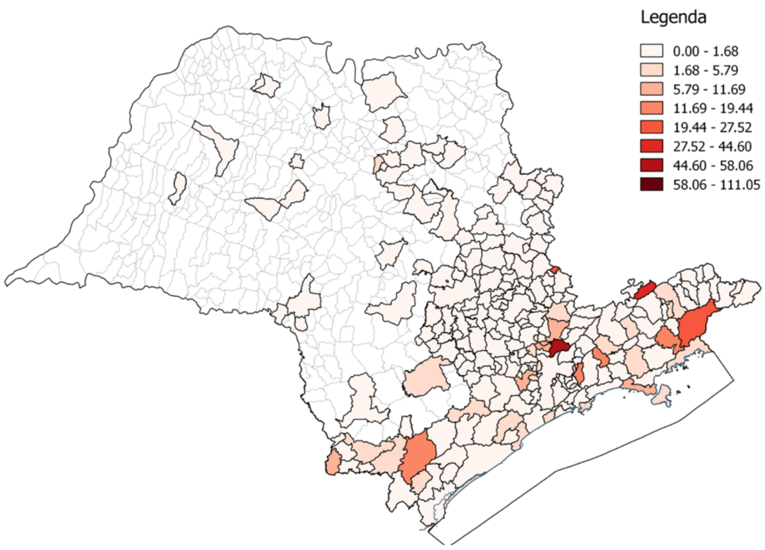

Figure 34 - People living in risk condition R4 per 1000 inhabitants

Normalizing the number of people at risk per the city inhabitants the value get stable statewide, with few exceptions for some cities of the "Vale do Ribeira" and the "Vale do Paraiba".

It is possible to have a more exhaustive view looking at a map considering an equivalent number of people at risk. The formula of this indicator is:

$$Req = 0{,}05R1 + 0{,}25R2 + 0{,}5R3 + R4$$

This indicator has been constructed, to keep into stronger consideration people living in a worse condition, analyzing the historic of intervention in each city and comparing it with the number of people living at risk according to preparatory plans.

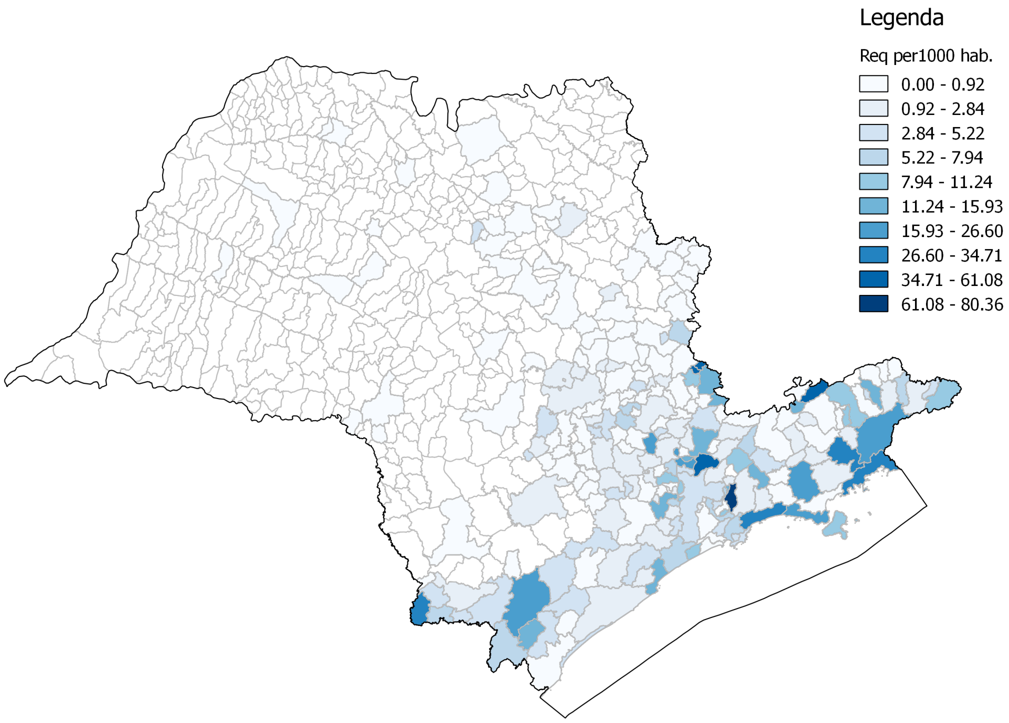

Figure 35 - Equivalent number of people living in risk condition per 1000 inhabitants

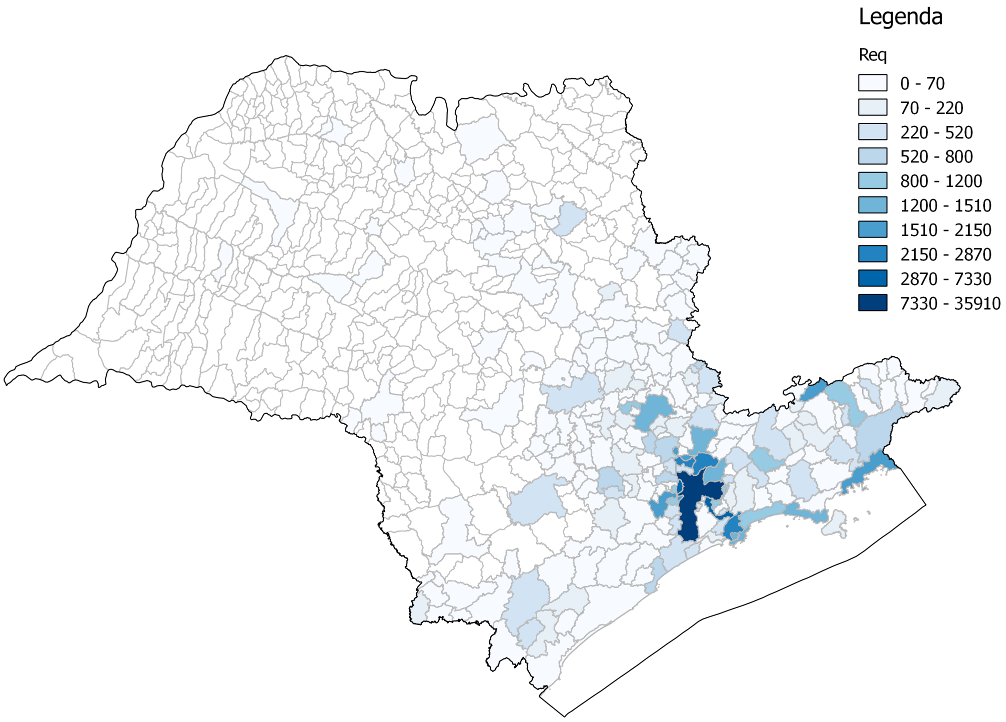

Figure 36 - Equivalent number of people living in risk condition

A higher attention has been given to people living in condition of high risk. CPRM-made preparatory plans does not includes people in condition R1 and R2. This would need to be kept in consideration in the next steps, especially because Campinas risk mapping, one of the biggest São Paulo state cities has been done by CPRM.

The São Paulo State government identifies 208 city needing of particular attention. And identifies 2 kinds of attention areas, flooding attention areas and landslide attention areas. These areas monitored with more attention and the COMDECs prompter.

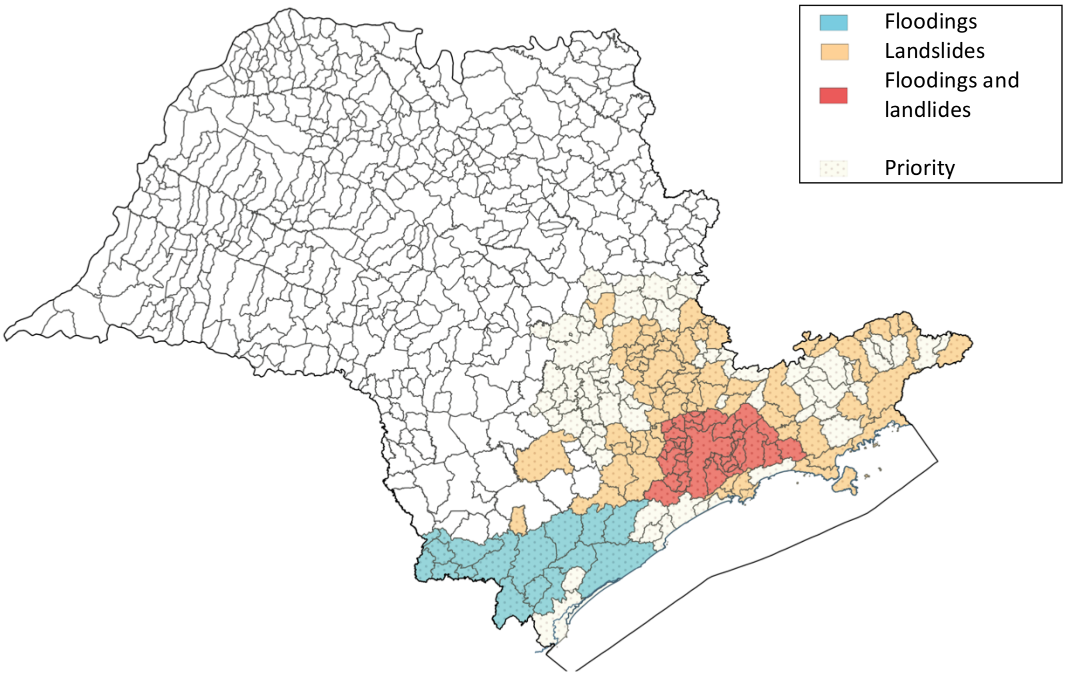

Figure 37- Priority cities and areas of attention

Resuming, São Paulo State counts 645 cities, organized according to the Civil Defense in 19 REDECs, of which, 365 needed at least an intervention from the Civil Defense, and of 195 is known the number of people living in a condition of risk. About 28,26 million people lives in cities which number of people at risk is known (about 65% of the state population).

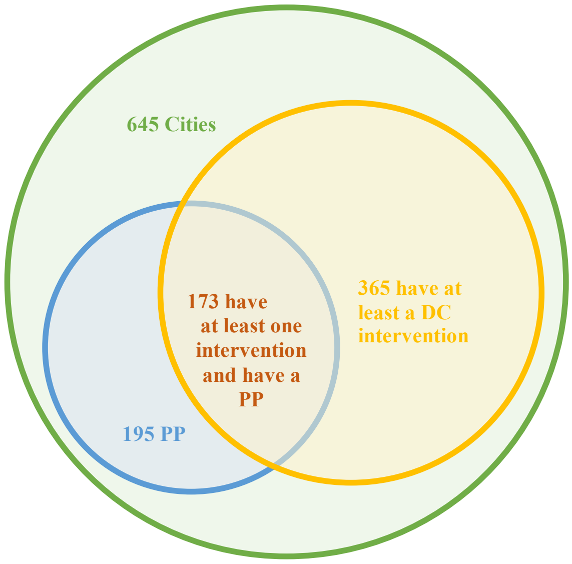

Figure 38 – Available data

In order to estimated the demand of relief supplies and have an effective localization of the warehouses statewide, is needed to known the people at risk in the whole state, with a municipal resolution, this information however is not directly available. It is possible to think to exploit the intersection between these two subsets to calculate an estimation of the people at risk in the whole São Paulo State.

3.4.3. HUMAN DEVELOPMENT INDEX

It is possible to perceive that especially while considering the south region, the number of people at risk, interventions and affected people per 1000 inhabitants is get higher as the city HDI get lower.

HDI is a composed statistic of life expectancy, education and per capita income. These factors strongly influence people capacity to be prepared and respond to natural hazard.

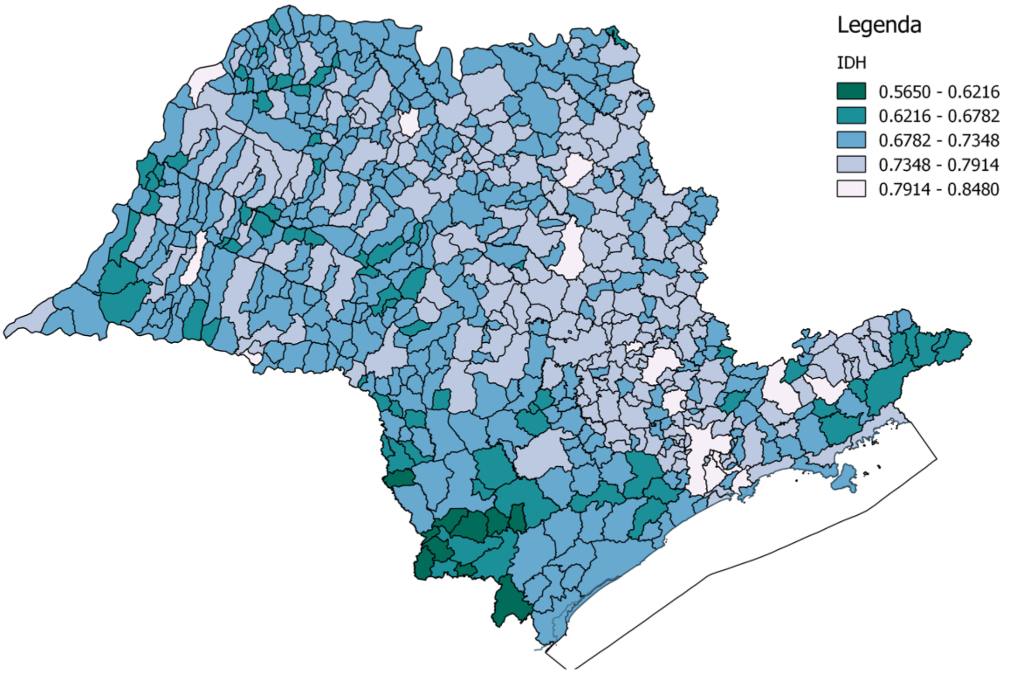

Figure 39 – Human Development Index per city

4. METODOLOGY

After an analyses of the available data, a stochastic optimization model has been developed.
The model aims to choose the deposits best locations between a set of possible ones, minimizing the total of operational and installation cost.
The demand of supplies will depend only on the number of people considered as affected by the disaster.
Constraints of maximum distance between warehouse and demand point are taken into account. The best location is chosen independently from the deposit capacity.
A stochastic optimization model has been chosen, that will evaluate scenarios with different disaster magnitudes. Their probability of occurrence will be estimated according to Civil Defense historic of interventions.
In order to choose the best localization, the number of people at risk of each city of the state should be known. Unfortunately, this information is not available statewide.
The solution suggested in this work is to exploit the set of cities having both risk mapped and historic of Civil Defense interventions to extrapolate a relation between the historic of interventions and the persons at risk.
Advanced regression models are used for this purpose. For each category of risk, a function connecting the number of people in that level of risk (dependent variable) to the historic of Civil Defense interventions (independent variables) is formulated. The entries of the historic entering the model, or compositions of them, are chosen in order the maximize the model fitting quality. Cities not having a risk mapped and never needed Civil Defense intervention (not present in the historic) will be considered at zero risk, id est, these cities have no people living a risk condition. Anyway, in the mathematical optimization model the constraint of maximum distance between warehouse and these cities must be respected.

5. OPTIMIZATION MODEL

5.1. STOCHASTIC MODEL

The model objective is to determine the best place where to locate disaster relief supplies Civil Defense warehouses. It consists in a two-stage stochastic optimization model, in the first stage the installation location is decided, in the second stage the demand generated in the scenarios is attended.

The objective function minimizes the total annual cost of the warehouses, composed by three term, annual depreciation, stock management costs and transportation costs.

The dimension of the problem (169 possible candidate deposits, 645 demand point, 6 scenarios) needed a mathematical model being at the same time effective and simple enough to be run in an acceptable amount of time by a commercial computer.

The problem model is based on the ones studied by Brito Junior, Leiras, and Yoshizaki (2013), applied to the region of "Vale do Paraiba" (coinciding with REDEC I-09), and Balcik and Beamon (2008).

The author chose to not consider constraints in deposits or channel capacity due to static nature of the model. Due to the structure given to the scenarios in order to keep their number the lower possible, the annual demand for disaster relief supplies generated by the category of disaster considered in the scenario collapse in a single event. This would led, in this case, to misleading conclusions.

5.1.1. MODEL DESCRIPTION

5.1.1.1. Sets:

I: Candidate warehouse locations ($i \in I$)

J: Demand points, cities ($j \in J$)

C: Scenarios ($c \in C$)

5.1.1.2. Decision variables

First stage variables

X_i: Binary variable, indicates if the i-th location should be opened a deposit (non-dimensional)

Second stage variables

A_{ij}: Binary variable, indicates if the warehouse in location i attends the j-th city

5.1.1.3. Parameters:

t_{ij}: Travel time between location i and city j (minutes)

d_{ij}: Distance between the location i and city j (kilometers)

$demand_{ij}^{c}$: Demand of supplies of the city j in the scenario c

$tcost_{ij}^{c}$: Cost of transporting a the demand D_{ij}^{c} from deposit i, to city j

$whcost_i$: Warehouse i installation cost

$whmancost_i$: Warehouse i and stock management cost

ny: Warehouses lifetimes

$whmax$: Maximum number of open warehouses

$whmim$: Minimum number of open warehouses

t_{limit}: Limit travel time to attend a city

$bigM$: Big M used in the iff constraint

5.1.1.4. Objective function

Minimizes the warehouses fixed costs more the second stage objective function minimizing for each scenario the transportation costs:

$$\min \quad \sum_{i} \left(\frac{whcost_i}{ny} + whmancost_i \right) X_i \; + E^c[\,Q] \tag{1}$$

$$Q(c) = \min \sum_{ij} tcost_{ij}^{c} \; A_{ij} \tag{2}$$

5.1.1.5. Constraints:

Inferior limit for number of open warehouses:

$$\sum_{i} X_i \leq whmax \tag{3}$$

Superior limit for number of open warehouses:

$$\sum_{i} X_i \geq whmin \tag{4}$$

Bilateral connection *iff* a deposit is open if and only if it attends at least a city in each scenario:

$$\forall i \quad \sum_{j} A_{ij} \geq X_i \tag{5a}$$

$$\forall i \quad X_i \; bigM \geq \sum_{j} A_{ij} \tag{5b}$$

Each city has to be attended by at least a warehouse in each scenario:

$$\forall j \quad \sum_{j} A_{ij} \geq 1 \tag{6}$$

Each attend city should be reachable in a time smaller than the limit travel time in each scenario:

$$\forall i, j \quad t_{ij} \, A_{ij} \leq t_{limit} \tag{7}$$

A further constraint of mandatory opening of a warehouse in a certain location could be added, an example is:

$$X_{São \; Paulo} = 1 \tag{8}$$

5.1.2. MODEL IMPLEMENTATION

The model has been implemented through the commercial software AIMMS version 4.6. And solved with the CPLEX 12.6.1 solver.

5.2. MODEL PARAMETERS DESCRIPTION

5.2.1. SCENARIOS

Six scenarios are evaluated; each scenario considers a disaster of a different magnitude and impact. As much as the magnitude increases people in lower risk condition are the disaster considered affected:

- Level I = 10% of people in condition R4 affected;
- Level II = 50% of people in condition R4 affected;
- Level III =100% of people in condition R4 affected;
- Level IV = People in condition R3 and R4 are affected;
- Level V = People starting from R2 are affected ;
- Level VI = The totality of people living in a condition of risk, even if low (R1), are affected by the disaster

The probability of each disaster is estimated using Civil Defense historic of interventions. Each intervention has been classified according to the number of people living in risk condition affected by the disaster that caused the intervention, according to the six levels of disaster magnitude (each intervention is relative to the occurrence of a natural event in a single city).

5.2.2. DEMAND

The demand for relief material has been estimated according to the number of people hypothetically affected by the disaster in each scenario. Each affected person needs to be supplied with a Relief Kit, considered as the model “supply unit”, consisting in each of the individual kits (Dressing Kit, Bedding Kit) and a fourth of the kits shipped per family (Cleaning Kit, Hygiene Kit, Basic Food Basket).

5.2.3. TRAVEL TIME AND DISTANCE

In order to make the model more realistic the estimation of travel time and distance have been made through internet based routing tools, the OSRM service has been used, based on open data from OpenStreetMaps database. This permitted to take into account the road quality and the state topography.

OSRM allows with a single request to have all the data about the route from a point to another, given latitude and longitude of the 2 points. The resulting travel time considering a car as transportation vehicle. Due to the different kind of vehicle shipping the relief supplies, data needed to be adapted. The resulting average speed in our routes resulted to be of approximately 80.5 km/h. The average velocity of 50 km/h has been considered per truck responsible for the freight. Therefore, the travel time needed a correction of a multiplicative factor of 1.54.

The information about latitude and longitude has been gathered thanks to the Google Maps free geocoding service. For each city have been considered, with the exception of São Paulo, where latitude and longitudes refers to the approximate location of the existing deposit.

5.2.4. MAXIMUM WAREHOUSE – CITY DISTANCE

The maximum travel time has been estimated together with CEDEC-SP, considering the ideal time to ship the materials and the maximum acceptable one. Being the Civil Defense not responsible for the immediate response to the disaster, according to CEDEC-SP the relief materials need to be shipped in at the most 8 hours, 2 of them needed for the preparation of the load and the truck loading. It has been considered a limit travel time of six hours.

5.2.5. TRANSPORTATION COST

The transportation cost has been estimated using data from the "Câmara Técnico Econômica da Associação Nacional de Transporte de Cargas e Logística" (NTC,2014). A function considering function has been regressed from NTC published data. The regression fitted very well the tabled data, showing a value of the Adjusted R2 indicator equal to 0.998.

$$tcost_{ij}^{c} = 10.34 + 3.384 \cdot 10^{-1} demand_{ij}^{c} + 1.191 \cdot 10^{-2} d_{ij} + 3.823 \cdot 10^{-4} demand_{ij}^{c} \cdot d_{ij}$$

5.2.6. WAREHOUSE COSTS

The cost of implementation has been considered as the cost of the canvas warehouse itself, informed by the CEDEC-SP, more the cost of the internal equipment of the warehouse and their preparation. The cost have been spread on the canvas lifetime, according to the standard lifetime of commercial warehouse canvases.

The warehouse annual management has been considered according to Brito Junior (2015).

5.2.7. NUMBER OF WAREHOUSES

According to CEDEC-SP, the number of relief supplies CD warehouses statewide should coincide at the most with a warehouse for each REDEC of the “Interior” of the State, plus the central one, located in São Paulo. That way the maximum number of warehouses has been set to 16. The minimum number have been set to five, according to CEDEC-SP indications.

6. DATA PROCESSING

6.1. REGRESSION PROCESS

6.1.1. REGRESSION WORKFLOW

In this section of the chapter, the regression process used to define the function predicting the number of people living in a risk condition for the cities featuring the historic of interventions, according to the four categories defined in the municipal preparatory plans.

$$People\ at\ Ri = f_i(available\ data) \qquad i = 1,2,3,4$$

This estimative is at the basis of the optimization model. The data about people living in risk condition statewide is used to compute the relief supplies demand of each city and the probability of each scenario.
Using as sample the subset of cities featuring both data about historic of interventions and risk mapping, four iterative regression processes, testing a series of regression models, have been implemented. The sample size will therefore coincide with the number of cities in the subset (173 cities).

The first step consisted in choosing from the available data that should be independent variables in the regression models. The available data can be separated in two categories:

- Historic data per city:
- Demographic data:
    - Population
    - Average density of the city
    - Human Development Index

Given the relatively small size of the sample compared with the number of predictors, according to the law of parsimony, the number of predictor variable should be as low as possible, in order keep the model as simple as possible, but high enough to give significance to the model.

Four variables have been considered to enter the model: the number of affected people, the number of interventions, the population of the city, and the human development index.

Predictor variables	Assumption
Affected people	The number of people affected by a disaster is a part of the people that according to a municipal preparatory plans live in a risk condition
Number of interventions	An higher number of people living in a risk condition cause an higher number of interventions
Population	People living in a risk condition is a part of the total population, city with an more inhabitants usually show an higher number of people living in a risk condition
Human Development Index	Being HDI a composed indicator of education, life quality and wealth of the city it is an indicator of the capacity of the population to face an hazard

Table 1 – Predictor variables

In the estimation of people living in condition R4, we will see that the use of these aggregated values is not sufficient go give statistical significance to the regression model. The case will be discussed in the dedicated section of the chapter.

From this moment forward R1, R2, R3, R4 will indicate also the variable counting the number of people living in the respecting condition of risk, it is left to the reader to deduce from the context if the author is referring to the variables or to condition of risk if not explicitly declared.

6.1.1.1. Linear regression model

A linear regression multivariable model has been developed, and the quality of the model tested according to two quality indicators Adjusted R^2 and the normality of the residuals. It can be noticed that considering the interactions and the quadratic values of the predictors variables the value of Adj R^2 grows up 0.96 in some models, while considering the residuals, they presents heavy tails and in any model can be considered as normally distributed. Normal distribution of the residuals is the main assumption at the basis of the statistical test usually

used to estimate the model fitting quality and the statistical significance of the coefficients of the models. Although Lumley et al. (2002) affirms that is the size of the sample is high enough (i. e. higher than 15) the output of the model continues being valid, the author preferred to use others estimation techniques.
Even because the coefficient of the linear models resulted of difficult interpretation, and very far from the expected values.

6.1.1.2. Generalized regression model and dependent variable distribution:

This lead to the evaluation of more complex models, generalized linear models.. The first step has been to fit available data for the dependent variables with the most appropriate statistical distribution.
People living in risk condition is a variable composed of integer values, always non-negatives, with a higher density as getting closer to the zero. This identifies the variable as a count variable.
Fits with Poisson distribution and negative binomial distribution have been visually tested on the data and on transformations of them, comparing the empirical cumulative distribution function with the theoretical one.
From the graphs can be inferred that the negative binomial fits the empirical distribution better with respect to the Poisson distribution, because of the relaxation of the constraint on the variance of the distribution. Can be noticed that by considering the number of people living in a risk condition per 1 million inhabitants (usually in the work data are considered per 1000 inhabitants, in this case this particular relativization allows to keep the variable count) the fit with the negative binomial distribution improves significantly.

The process leading to the final model consisted in an iterative process of development of regression models and comparative evaluations. Non-nested models have been evaluated according to Vuong Test. It is worth to remember that generalized linear regression models with dependent variable distributed according to Poisson and negative binomial distribution can be considered nested models (Dobson 2002).
Even if the negative binomial distribution fits better the dependent variable data, the regression model for Poisson distributed dependent variables will be always calculated in parallel. Even if will be demonstrate that considering the same independent variables the

generalized linear regression model for negative binomials distributed dependent variables always has a better fit of the data. This complication is kept because for the Poisson GLM is possible to compute Mc Fadden's pseudo R2, a regression fitting quality indicator that can be interpreted in an identical way to his more known relative Adjusted R2.

After several tests it has been identified that the best way to express the dependent variable is to consider it relativized per 1000 inhabitants, even if this transformation would led to the loss of the feature of count variable, this issue can be solved with a simple mathematical trick.

Because of GLM uses transformation of the dependent variable by mean of link functions, and the link function for count data is the natural logarithm the regression model will result in:

$$\log(dep\ variable) = \sum_i coeff_i \cdot indep\ variable_i$$

$$\log\left(\frac{dep\ variable}{\frac{Population}{1000}}\right) = \sum_i coeff_i \cdot indep\ variable_i$$

$$\log(dep\ variable) = \sum_i coeff_i \cdot indep\ variable + \log\left(\frac{Population}{1000}\right)$$

In this case the term $\log\left(\frac{Population}{1000}\right)$ is considered as an offset of the regression, and statistical software have options to consider it in the model.

Models with an incremental number of variables have been testes until getting to the saturated model considering all the three variables. The model presenting the highest statistical significance of the coefficients and presenting the best fit according to F-Test has been chosen as the best-possible generalized linear model

6.1.1.3. High number of zeros and zero inflated models

Give the high dispersion of the data, and the high frequency of zeros in the dependent variable zero inflated regression models have been tested. Poisson e negative binomial generalized linear regression model are nested model for their respective zero inflated versions. According to Vuong Test, corrected according to Akaine criterion, zero inflated version of the model always works better in regressing the given data.

6.1.1.4. The tools used

To implement the regression model, the software R was used. The distribution best fitting the data has been computed using the *fitdist* R function, in the package *fitdistrplus*. In order to fit the relativized variables with a negative binomial a mathematical trick has been necessary, *fitdist* function is able to compute the best fitting negative binomial distribution only if the variable is count, but the variables per 1 000 inhabitants presents manyof not integer values. A further transformation was needed, it was considered the number of people per 1 000 000 inhabitants rounded to its closer integer, in order to have the minimum loss of information. This transformation anyway, did not change the meaning of the fitting.
Regression models have been calculated with the functions:

- Generalized linear model for Poisson distributed dependent variables: *glm* included in the R software.
- Generalized linear model for negative binomial distributed dependent variables: *glm.nb* from the package *MASS*.
- Zero-inflated models: *zeroinfl* function from the *pscl* package.

6.1.2. REGRESSION MODEL FOR THE PEOPLE LIVING IN RISK CONDITION R1

6.1.2.1. Fitting

The data for the variable R1 present result concentrated between 0 and 2000, presenting a high frequency of zeros, a not so much is understandable from the histogram of the variables.

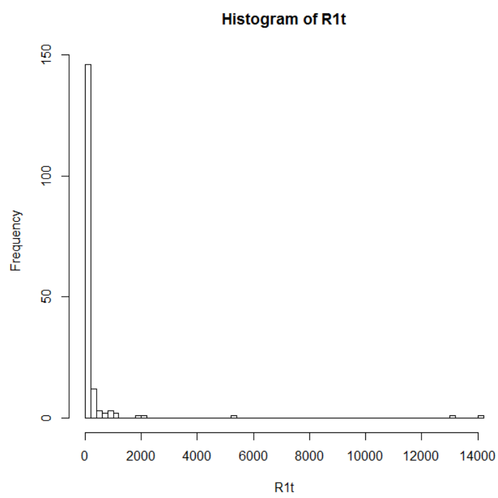

Figure 40 - Histogram of R1

The histogram of the relativized variables, i.e., the number of people living in condition R1 per 1000 inhabitants, can be seen in Figure 41. Also in this case can be notices the high concentration of zeros, or quite zeros data. No information about the distribution of the variable can be inferred.

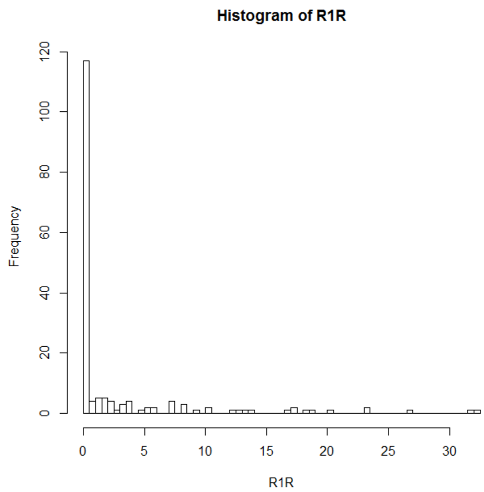

Figure 41- Histogram of R1 per 1000 inhabitants

It is possible to understand a little more comparing the empirical cumulative density function of the sample with the theoretical one of the supposed distribution best fitting the data. In Figure 42 and Figure 43 can be seen the data empirical density and cumulative density function compared with the its theoretical density functions according to the negative binomial distribution that best fits the dataset.

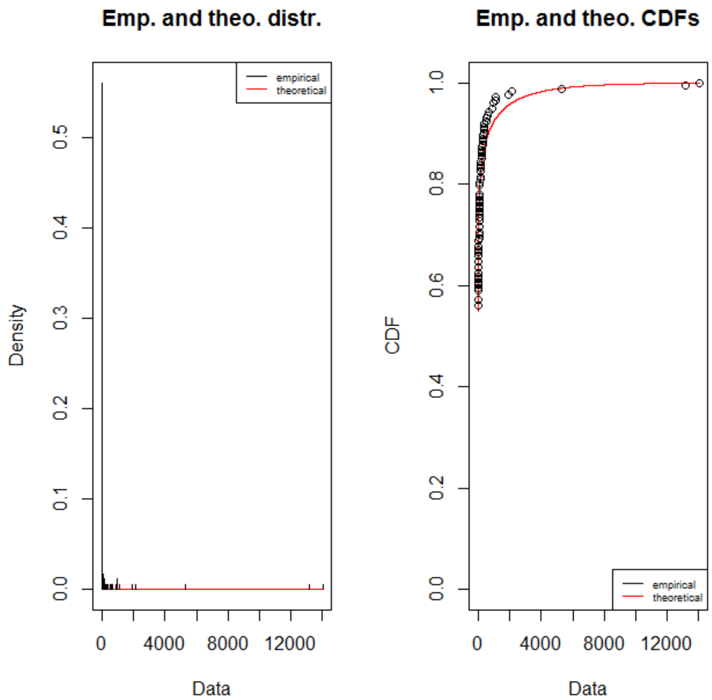

Figure 42- Comparison between empirical and theoretical DF and CDF for the variable R1 fitted according to a negative binomial distribution

It is possible to see that variable R1 has not a good fit with the estimated distribution function. For R1 relativized per 1000 inhabitants the fit improves slightly.

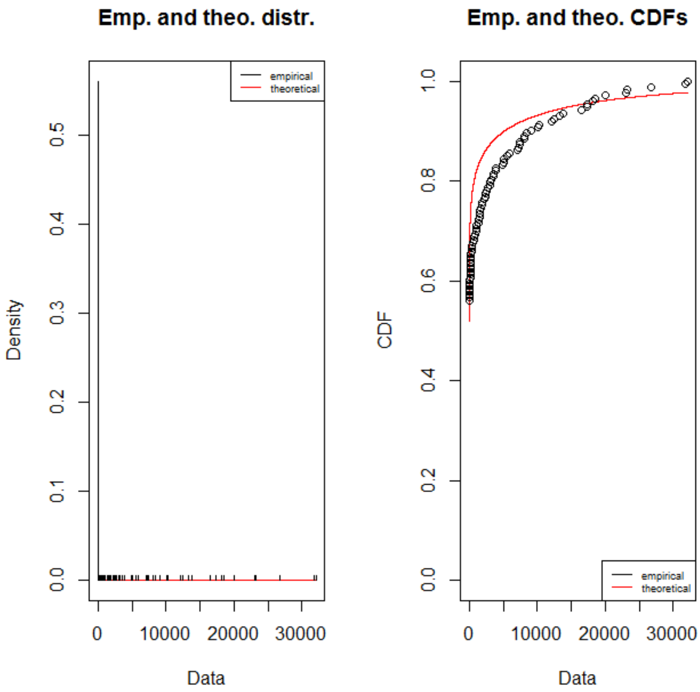

Figure 43- Comparison between empirical and theoretical DF and CDF for the variable R1 per 1000 inhabitants fitted according to a negative binomial distribution

Unfortunately, the same visual test has been done for the Poisson distribution, and the fitting quality does not result improved. Therefore, the generalized linear model referring to a negative binomial distribution will be used. After several tests the regression of the relativized variables showed better performaces.

6.1.2.2. Regression model

The model presents itself in the form:

$$\log\left(\frac{R1}{\frac{Population}{1000}}\right) = \beta_0 + \beta_1 \cdot Affected + \beta_2 \cdot Interventions + \beta_3 \cdot HDI$$

In Tabel 1 can be found the coefficient for the regression model and their respective F-test for the statistical significance.

	Estimate	Std.Error	z-value	Pr(>|z|)
(Intercept)	8.92E+00	4.19E+00	2.131	3%
Affected	4.19E-04	1.99E-04	2.101	4%

Interventions	2.88E-02	1.64E-02	1.749	8%
HDI	-1.18E+01	5.75E+00	-2.047	4%

Table 2- Coefficientets for R1 regression model with statistical significance

According to the regressed model the number of people living in condition R1 per 1000 inhabitants of a city can be estimated by means of an exponential functional with a linear exponent. It presents a positive intercept and is influenced positively, as expected, by the number of affected people and the number of intervention, and strongly reduced by the value of the Human Development Index of the city.

6.1.2.3. Regression diagnostics

Looking at the figure showing residuals vs fitted values, the residuals appear to have a strong trend, indicating that there are other factor influencing the variable that have not been considered in the model.

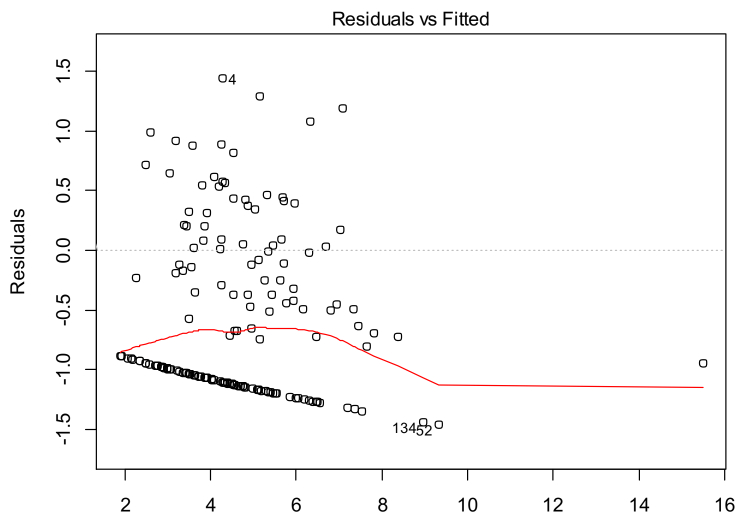

Figure 44 - Residuals vs fitted values for the R1 regressing model

The figure representing the normal quantile-quantile plot, present a particular morphology that if we were considering a common linear model would have been an indicator of bad quality of the model. The plot in figure does not differs from what expected for a negative binomial regression model. Searching for normality of residuals in a regression model of this kind would be misleading (Ben and Yohai 2004).

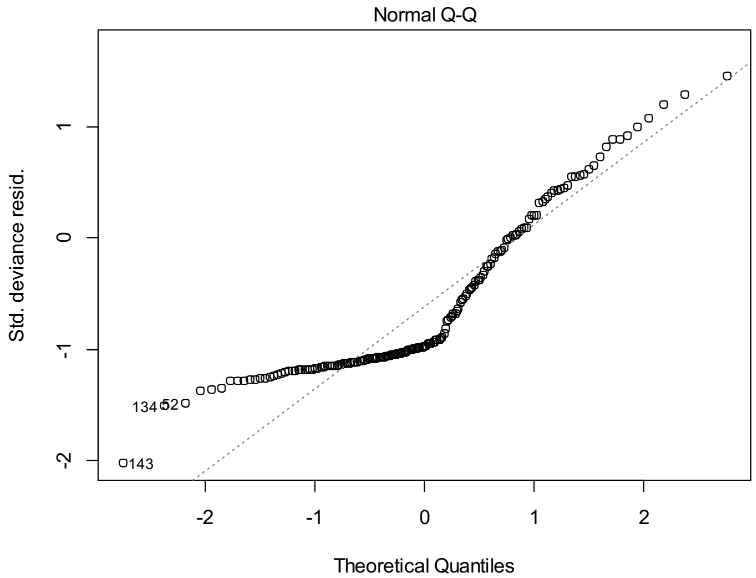

Figure 45 - Normal probability plot of the residuals for R1 regressing model

Looking at the plot residuals vs leverage show that there are not samples passing the limit thresholds, indicating that there are no outliers.

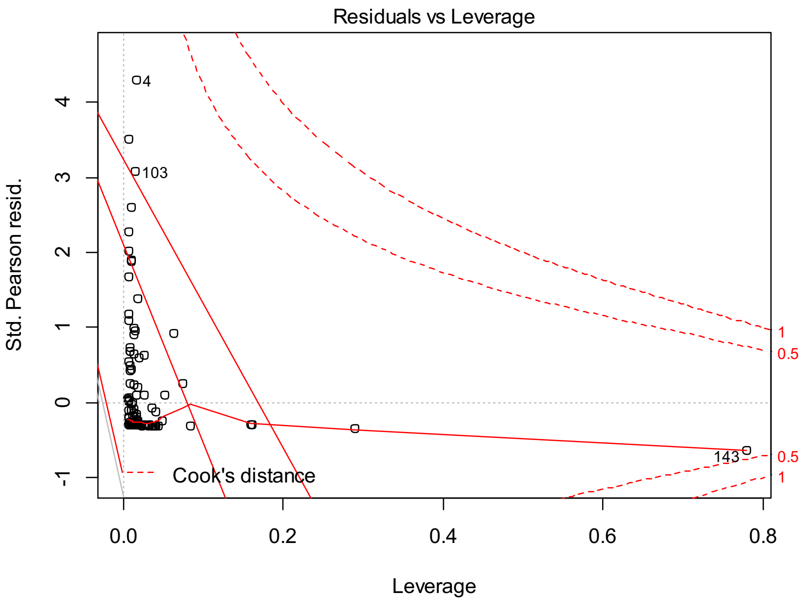

Figure 46 - Outliers diagnostic plot for R1 regressing model

Given the strong overdispersion of the variable a zero inflated model could be more appropriate, but due to the small influence over the final results of the model, the model will be considered.

6.1.2.4. Prediction for people living in condition R1

The prediction for the variable R1 is coherent with what expected looking at the historic of interventions and people affected. Both for the value per 1000 inhabitants that for the absolute one.

In the figures below, the value about the city of São Paulo has been exclude, given the high number of people living in risk R1. This allowed a better color resolution, resulting in a more effective representation.

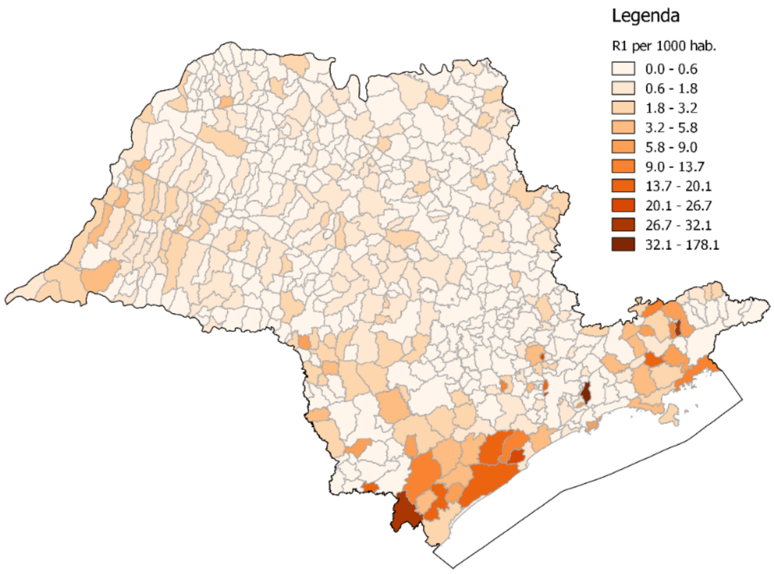

Figure 47 - Prediction for R1 per 1000 inhabitants

As expected the western region of the state present a high value of R1 per 1000 inhabitants, while due to the low population of the cities the absolute number results low.

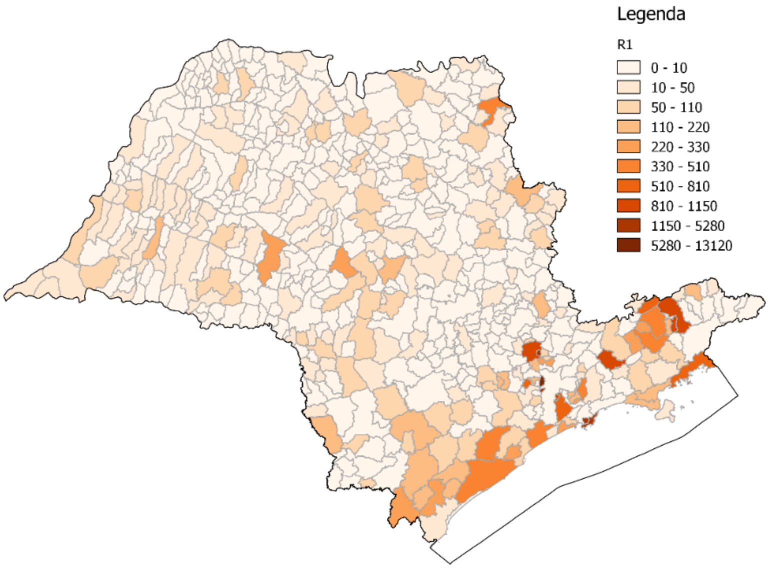

Figure 48 - Prediction per R1

6.1.3. REGRESSION MODEL FOR THE PEOPLE LIVING IN RISK CONDITION R2

6.1.3.1. Fitting

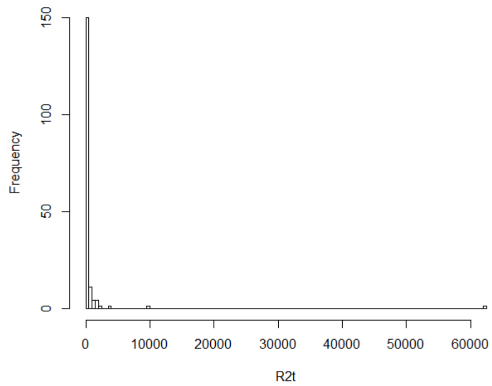

Figure 49- Histogram of R2

After having plotted the histograms in figures, especially looking at the relativized variable, the fit with the negative binomial seems to improve significantly with respect with the R1, phenomena of over dispersion of the variable and inflation of zeros values is still present.

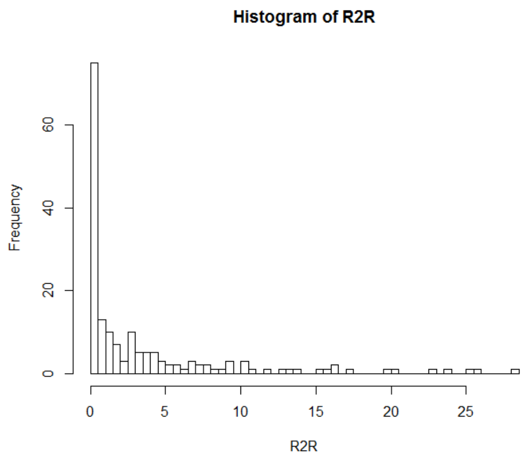

Figure 50- Histogram of R2 per 1000 inhabitants

Looking at the comparison between empirical cumulative distribution function and one of the best fitting negative binomial one, the fit seem quite interesting.

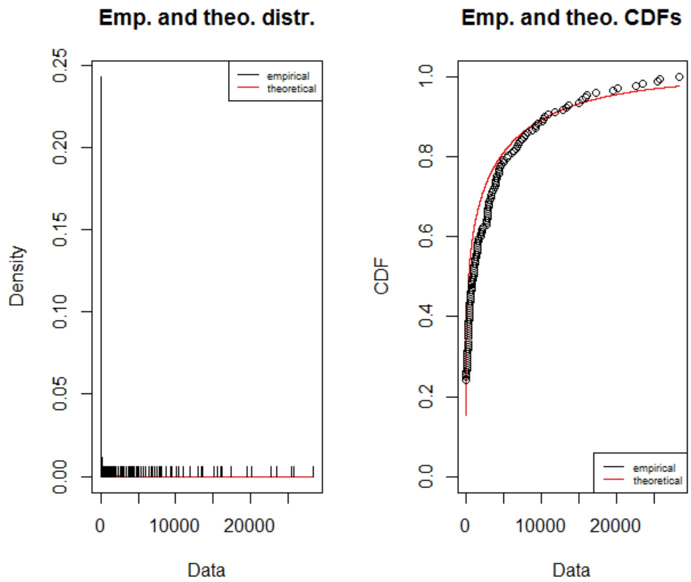

Figure 51- Comparison between empirical and theoretical DF and CDF for the variable R2 per 1000 inhabitants fitted according to a negative binomial distribution

6.1.3.2. Regression model

Also in this case, the model shows the following expression:

$$\log\left(\frac{R2}{\frac{Population}{1000}}\right) = \beta_0 + \beta_1 \cdot Affected + \beta_2 \cdot Interventions + \beta_3 \cdot HDI$$

With the following coefficients:

	Estimate	Std.Error	z-value	Pr(>|z|)
(Intercept)	7.87276	2.431522	3.238	0%
Affected	0.000193	0.000116	1.67	9%
Interventions	0.014758	0.009536	1.548	12%
HDI	-9.49579	3.338336	-2.844	0%

Table 3- Coefficients for R2 regression model with statistical significance

Also in this case, as for R1 the model behaves as expected. It has constant value reduced by the HDI value of the city, and increased by the number of people affected historically and the number of interventions.

6.1.3.3. Regression diagnostic

Also in this case a trend can be identified, showing that the model can be improved with other independent variables.

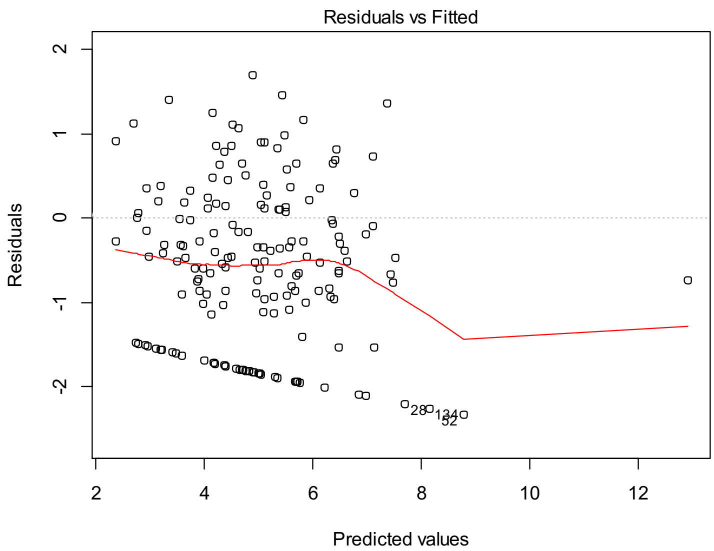

Figure 52- Residuals vs fitted values for the R2 regressing model

The quantile-quantile residuals normality plot shows the similar appearance to the one of the regression model developed for the variable R1, in this case the non-normality is less marked.

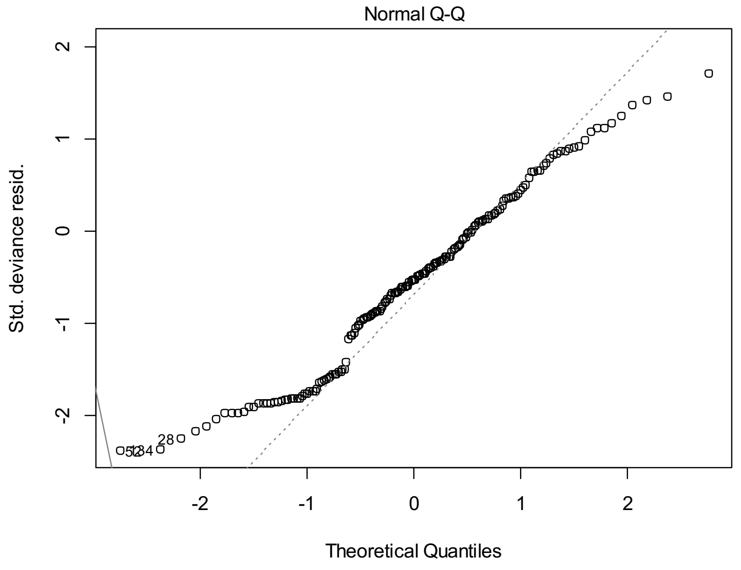

Figure 53- Normal probability plot of the residuals for R2 regressing model

The residuals vs leverage plot indicates that the sample 143, referring to São Luiz do Paraitinga could be a possible outlier. This caused its exclusion from the considered regression model.

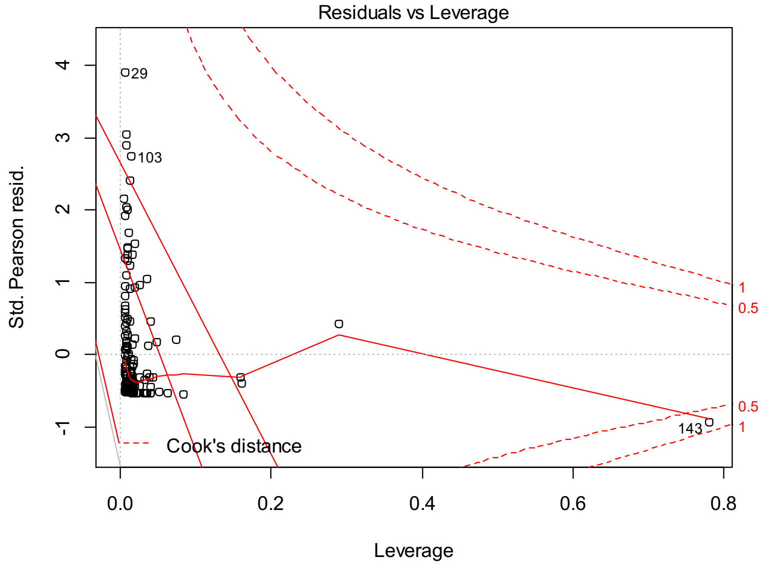

Figure 54- Outliers diagnostic plot for R2 regressing model

6.1.3.4. Prediction for people living in condition R2

Predictions of people at risk R2 is coherent with what expected.

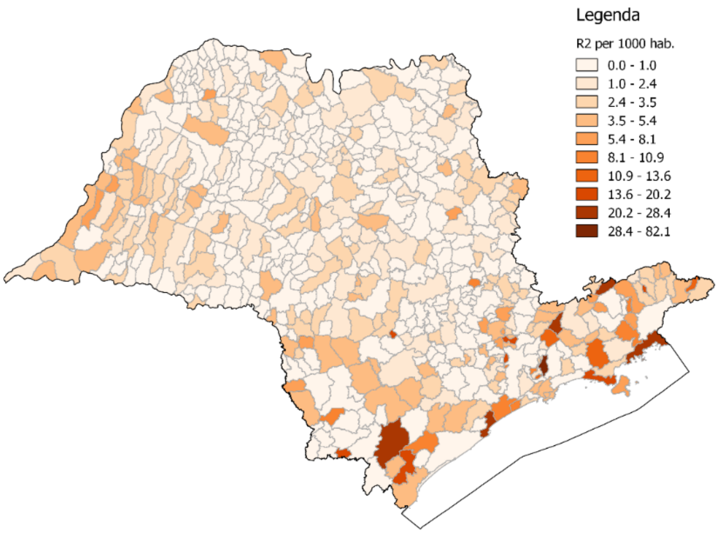

Figure 55- Prediction for R2 per 1000 inhabitants

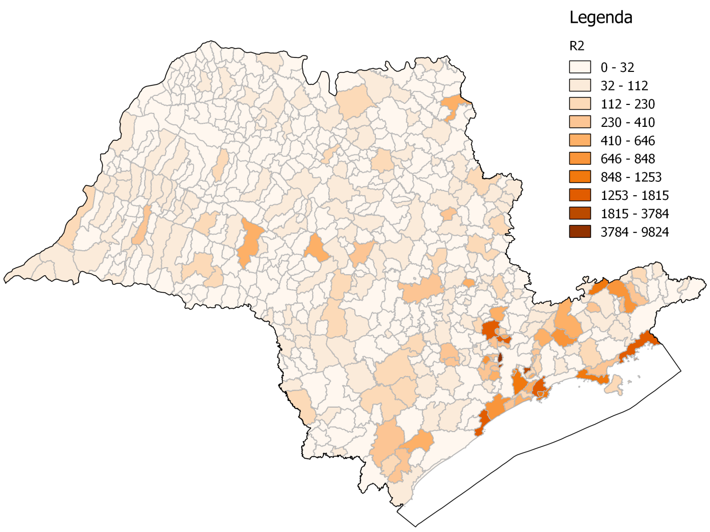

Figure 56- Prediction for R2

6.1.4. REGRESSION MODEL FOR THE PEOPLE LIVING IN RISK CONDITION R3

6.1.4.1. Fitting

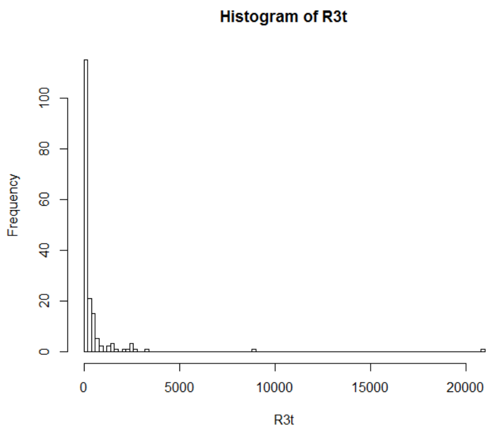

Figure 57- Histogram of R3

Looking at the histograms of the variable the fit with the negative binomil seems to improve, with respect to the two preious models, even if the zero inflation persists also in this variable, the data overdispersions got smaller.

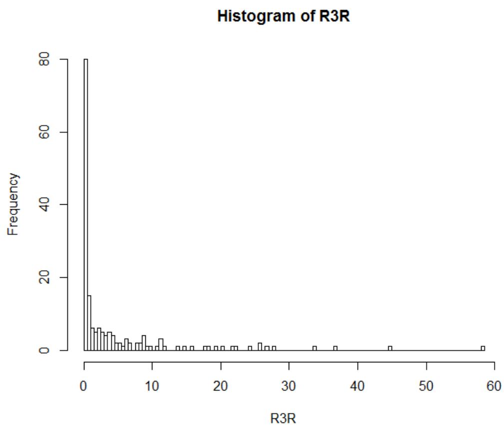

Figure 58- Histogram of R3 per 1000 inhabitants

The cumulative density functions show a good fit.

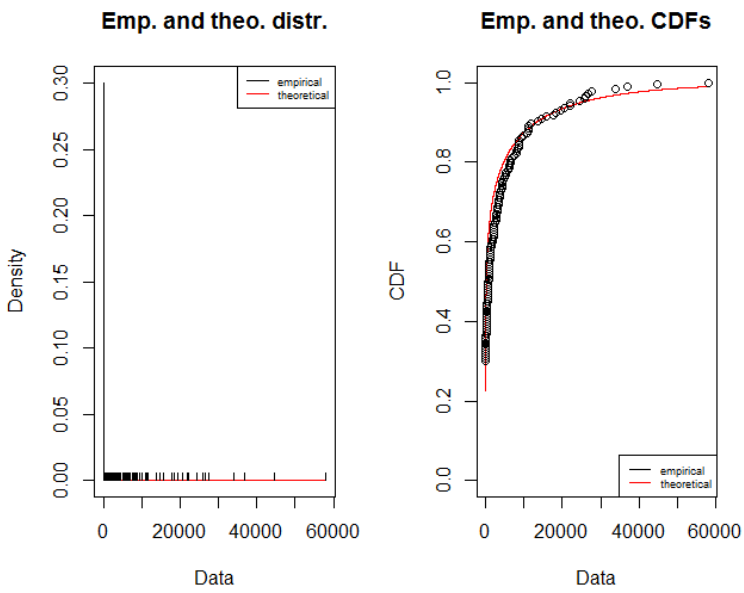

Figure 59- Comparison between empirical and theoretical DF and CDF for the variable R3 per 1000 inhabitants fitted according to a negative binomial distribution

6.1.4.2. Regression model

The regression model for this variable differs from the others. After various tests the model having a better statistical significance, depends only on the variable counting affected people.

$$\log\left(\frac{R3}{\frac{Population}{1000}}\right) = \beta_0 + \beta_1 \cdot Affected$$

	Estimate	Std.Error	z-value	Pr(>|z|)
(Intercept)	1.314172	0.183393	7.166	0%
Afetados	0.000221	0.000127	1.737	8%

Table 4- Coefficientets for R3 negative binomial regression model with statistical significance

6.1.4.3. Diagnostic

Diagnostic plots presents similar issues to the previous cases, no samples can be considered outliers for the model.

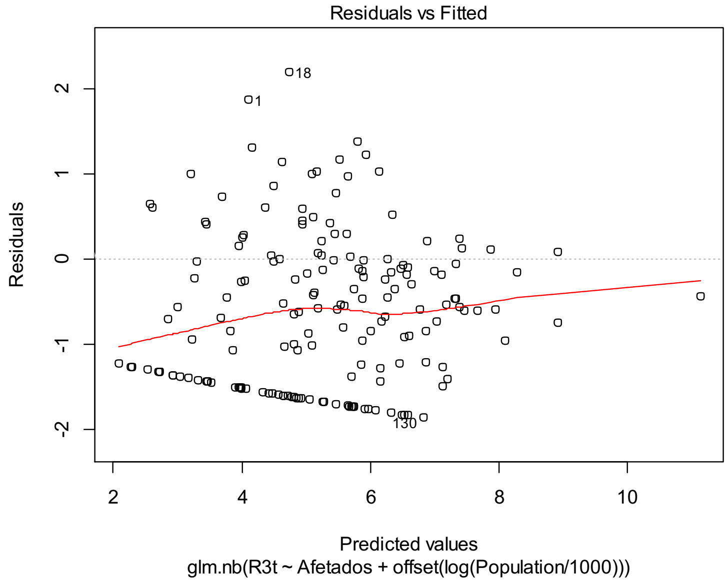

Figure 60- Residuals vs fitted values for the R3 regressing model

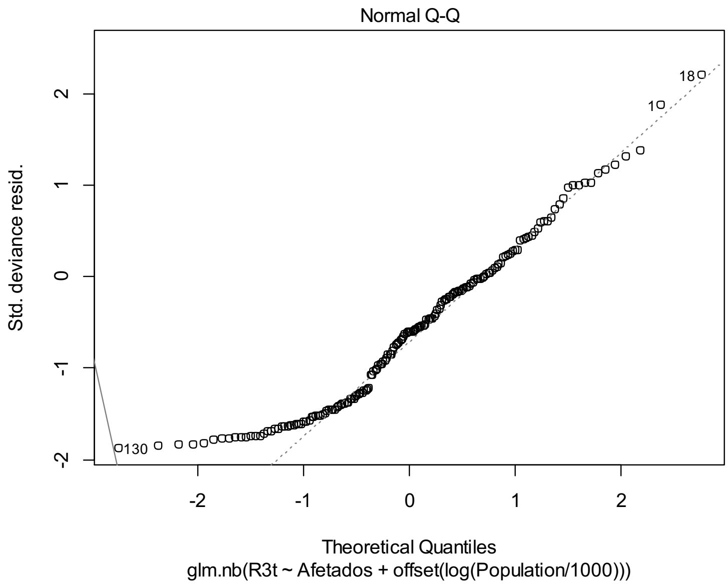

Figure 61- Normal probability plot of the residuals for R3 regressing model

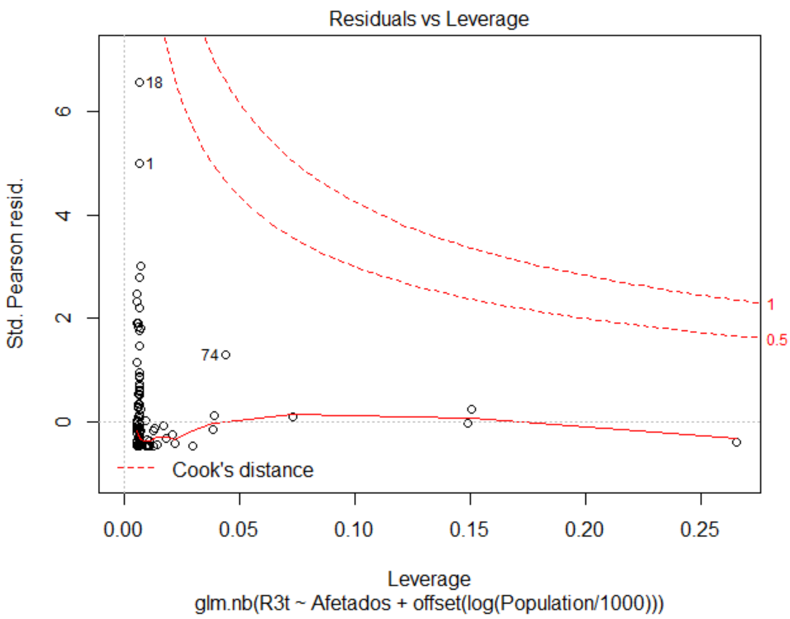

Figure 62- Outliers diagnostic plot for R3 regressing model

6.1.4.4. Prediction for people living in condition R3

The prediction of the variable R3 is coherent with what expected.

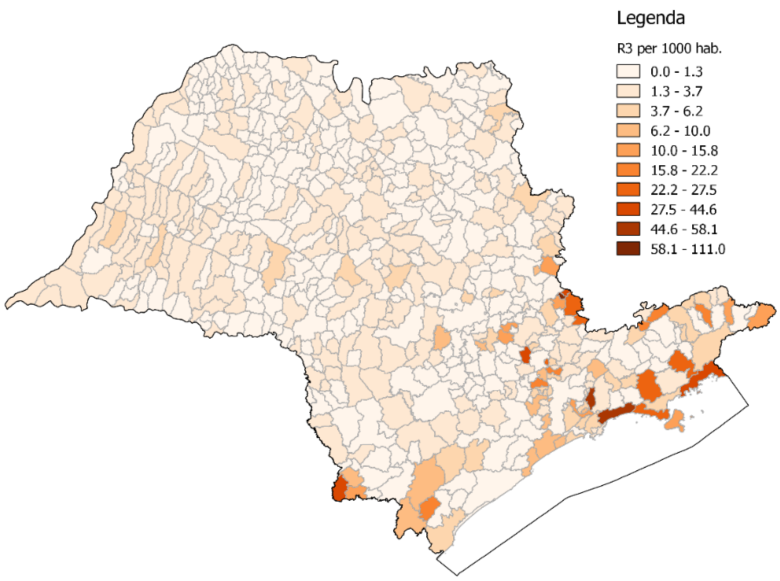

Figure 63- Prediction for R3 per 1000 inhabitants

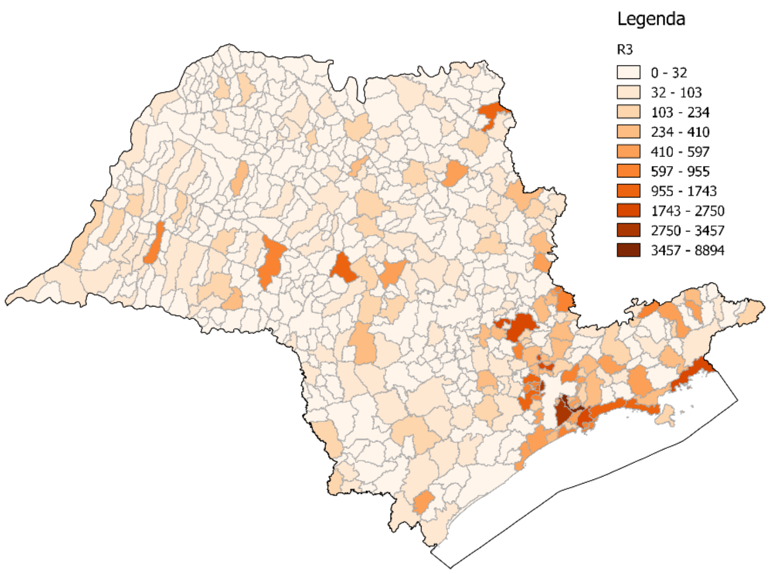

Figure 64- Prediction for R3

6.1.5. REGRESSION MODEL FOR THE PEOPLE LIVING IN RISK CONDITION R4

6.1.5.1. Fitting

In the histograms of the variable can be immediately identified a high over dispersion and inflation of zeros. This suggests the use of a zero inflated model.

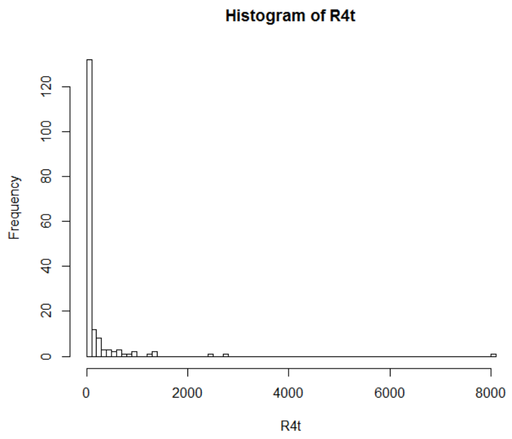

Figure 65- Histogram of R4

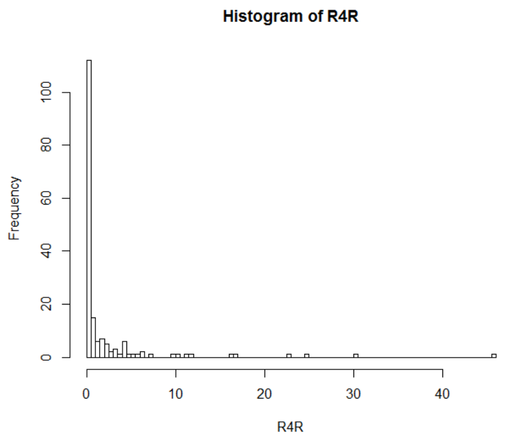

Figure 66- Histogram of R4 per 1000 inhabitants

Looking at cumulative density functions the fit with the best fitting negative binomial is very good.

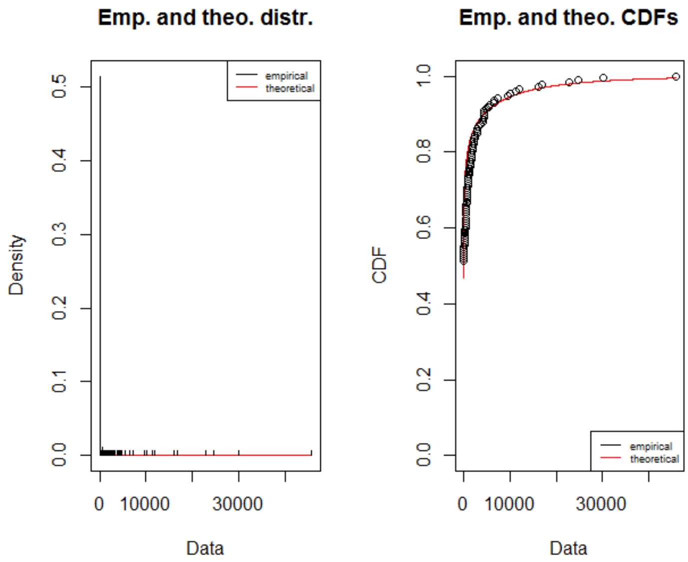

Figure 67- Comparison between empirical and theoretical DF and CDF for the variable R4 per 1000 inhabitants fitted according to a negative binomial distribution

6.1.5.2. Negative binomial regression model

In this case, the variables considered in the previous models were not able to represent the behavior of the dependent variable. All the variables in the historic of interventions were tested and the best regressive model resulted having the form:

$$\log\left(\frac{R4}{\frac{Population}{1000}}\right) = \beta_0 + \beta_1 \cdot Landslides$$

With the coefficients:

	Estimate	Std.Error	z-value	Pr(>|z|)
(Intercept)	-0.37736	0.24964	-1.512	13%
Landslides	0.31206	0.05074	6.15	0%

Table 5- Regression coefficients for the R4 negative binomial regressing model, with statistical significance

Diagnostic plots shows a trend in the residuals, as in the previous regressions, indicating that other variables should be included in the model. No outlier are shown from the residuals vs leverage plot.

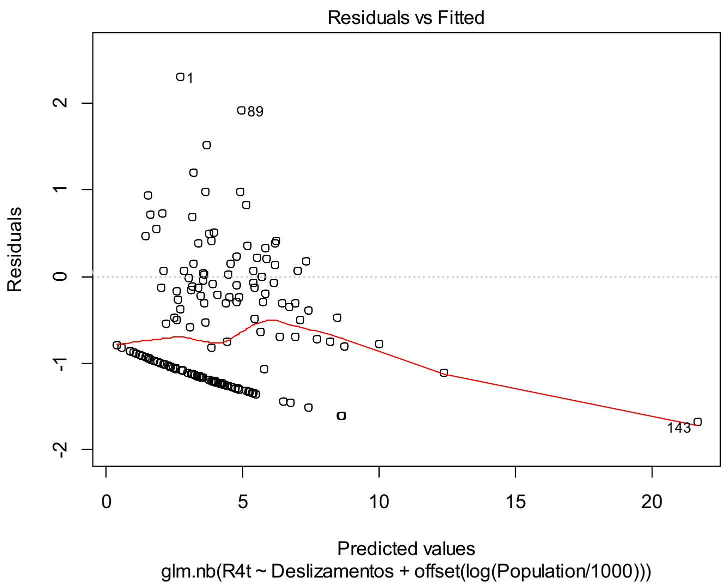

Figure 68- Residuals vs fitted values for the R4 regressing model

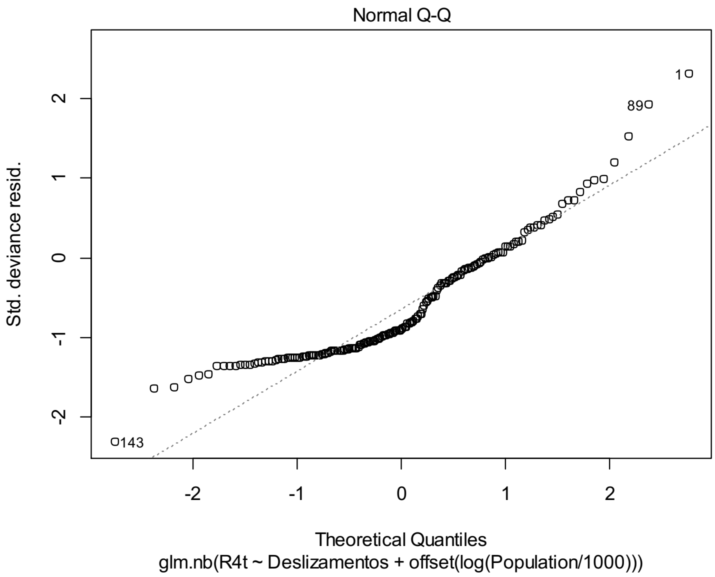

Figure 69- Normal probability plot of the residuals for R4 regressing model

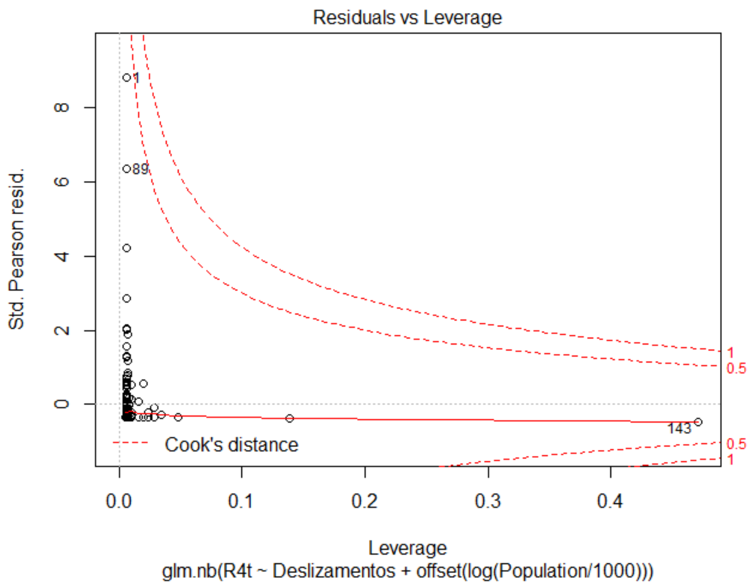

Figure 70- Outliers diagnostic plot for R4 regressing model

6.1.5.3. Zero inflated negative binomial regression model

A zero inflated has been considered to predict the number of people in condition R4, showing optimal result in the estimation of the coefficient. A comparison with the previous model through Vuong test showed that this model has a better fit.

	Estimate	Std.Error	z-value	Pr(>|z|)
(Intercept)	0.6399	0.2621	2.441	1%
DeslizamentosR	6.6999	2.8622	2.341	2%
Log(theta)	-0.9147	0.2241	-4.082	0%

Table 6 - Regression coefficients for the R4 count negative binomial regressing model, with statistical significance

	Estimate	Std.Error	z-value	Pr(>|z|)
(Intercept)	0.7407	0.2806	2.64	1%
Deslizamentos	-0.6119	0.2387	-2.564	1%

Table 7 - Regression coefficients for the R4 zeros logistic regressing model, with statistical significance

6.1.5.4. Prediction for people living in condition R4

The results are coherent with what expected.

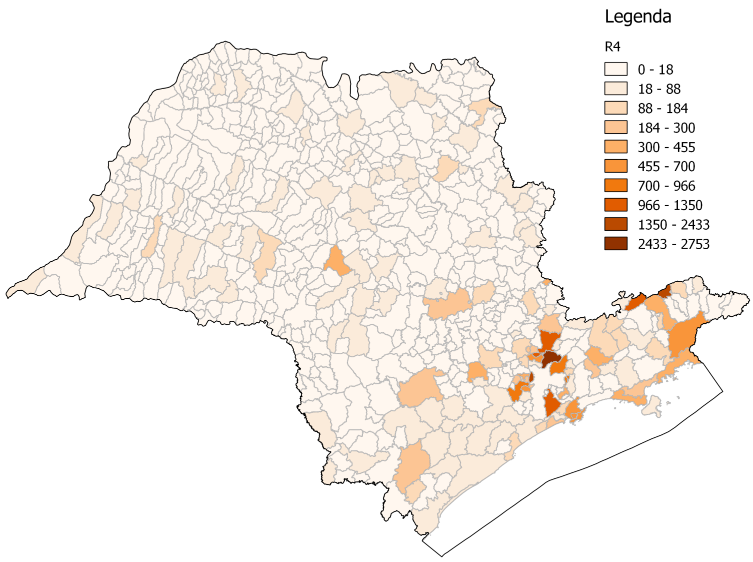

Figure 71- Prediction for R4

Particular attention as to be given to the city of Piquete, showing an anomalous number of people in condition R4 per 1000 inhabitants. The high number of interventions due to landslides per 1000 inhabitants influenced this value. Is has been decided to keep the value, but further investigation on the conditions of the city are suggested.

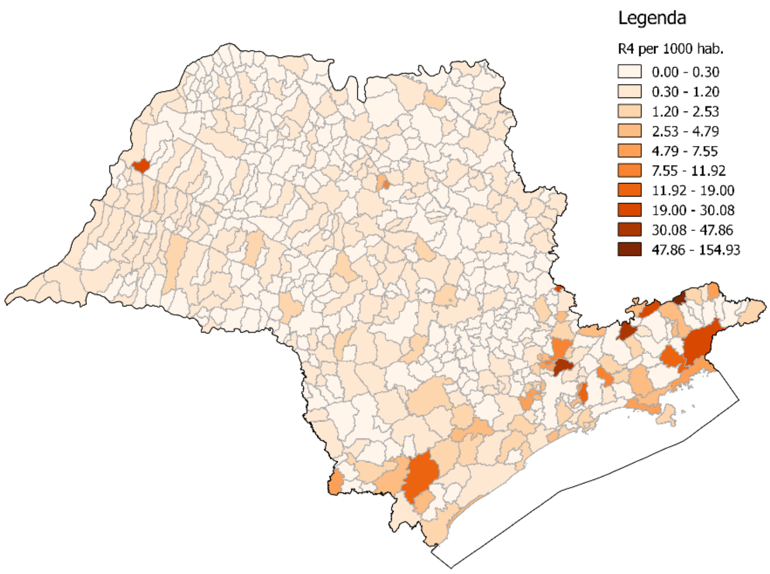

Figure 72- Prediction for R4 per 1000 inhabitants

6.2. HISTORIC ANALYSES AND SCENARIOS PROBABILITIES DEFINITION

6.2.1. CLASSIFICATION OF THE INTERVENTIONS

6.2.1.1. Classifications definition

In order to classify each intervention, four level of disaster have been defined, according to the proportion of estimated people living in risk condition affected during the natural event causing the interventions. These categories, coinciding with the level of the disaster, considers the magnitude of the disaster and its impact on the affected city. A higher level of disaster assumes that the population living in relatively safer condition is affected. Disaster of level n1, affects only people living in risk condition R4, disaster of level n2 affects also people living in risk condition R3, and so on. Level n4 considers as affected in additon the people living in risk condition up R1, other people not considered in municipal preparatory plans.

	R1	R2	R3	R4
n1				x
n2			x	x
n3		x	x	x
n4	x	x	x	x

Table 8- Disaster levels definition

6.2.1.2. Analyses of the historic of interventions

Each interventions has been classified according to the level defined in the previous section of the chapter. In order to take into consideration also intervention with a small number of people affected with respect other two categories have been defined:

- 0.1n1: in the disaster are affected less than 10% of the estimated number of people living in risk condition R4

- 0.5n1: less than 50% of the estimated number of people living in risk condition R4 affected.

In Figure 73 is shown the distribution of the interventions according to the levels of disaster defined.

More than the half interventions did not had any people directly affected by the disaster. Twenty percent involved less than 10% of the people living in risk conditions R4. The percentages of 0.5n1 and n1, would suggest that one of the two categories could be joint to an adjacent one. Anyway, the distinction between the two categories will be kept.

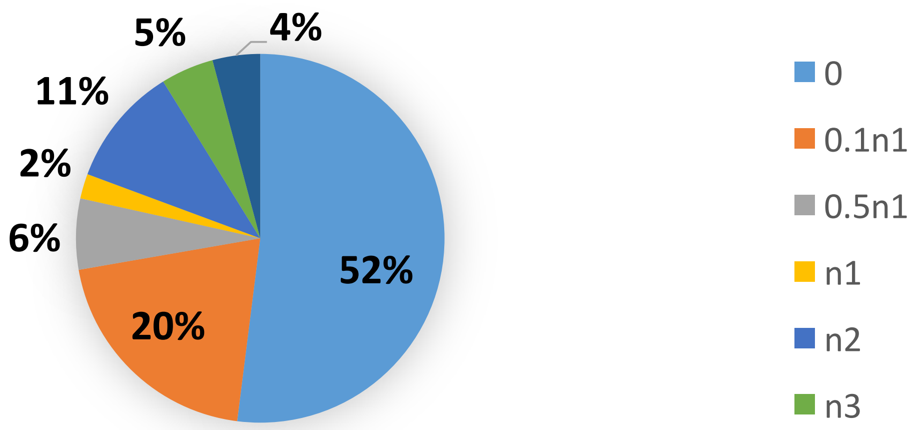

Figure 73 - Classification of the historic of interventions according to the level of the disaster

6.2.1.3. Probability of the disasters per level

The analyses shown in Section 6.2.1.2. is used to compute the scenarios probabilities.

Starting from the assumption:

- each calamitous events is represented in the historic as an interventions
- each calamitous events occurs during a single day
- calamitous events occurring in the same day, in different cities, even if close the one to the others, are reported as different interventions

By diving the number of interventions of each category by the total number of days for the years considered in the historic it is obtained the probability of encountering the day of occurrence of a disaster, for the considered category, in a year of the historic. In Figure 74 – Probabilities per category according to classification of the historic of interventionsFigure 74 can be seen the result of the calculation.

Assuming as constant the environmental conditions and excluding eventual annual trends in the occurrence of the natural hazards, this probability can be extended to the future years.

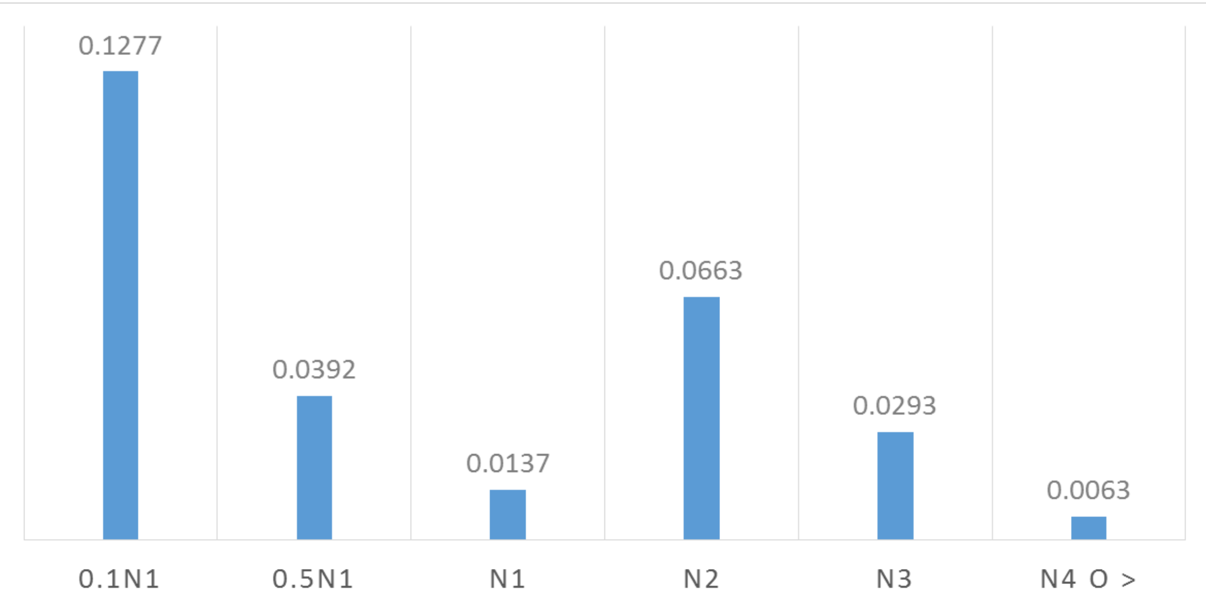

Figure 74 – Probabilities per category according to classification of the historic of interventions

6.2.2. SCENARIOS AND PROBAILITIES

The author defined six scenarios, one for each category considered in analyses of the historic of interventions. These scenarios represents the occurrence of a disaster affecting a number of people considered in the categories. The scenario has the same probability of the represented disaster computed in the analyses shown in the dedicated section of the work.

To define the number of people involved in the disaster, a worst-case scenario strategy has been followed. That means, the highest number of people belonging to category is always is considered as affected. Simulating the scenario relative to a disaster belonging to category n1, for example, that includes disaster in which are involved at the most all the people living in the R4 condition, the number of people affected in the scenario will coincide with all the people living in risk condition R4. Only exception is done for the scenario simulating events relative to category n4, the category considers also disaster with a number of people affected higher to the estimative of people living in a risk condition. The number of people affected in the respective scenario will be limited to the totality of the people estimated to live in a condition of risk.

Scenario	**Probability**	**Relative category**	**People affected**
I	0.1277	0.1n1	10% of R4
II	0.0392	0.5n1	50% of R4
III	0.0137	n1	R4
IV	0.0663	n2	R3+R4
V	0.0293	n3	R2+R3+R4
VI	0.0063	n4	R1+R2+R3+R4

Table 9 - Scenarios description and probabilities

7. RESULTS AND ANALYSES

7.1. RESULTS

7.1.1. MODEL SOLUTIONS

7.1.1.1. The optimal solution of the model

The model suggested a solution with five open warehouses, coincided with the lower bound set for the variable. Together with São Paulo, the cities chosen for the warehouses are Itapetininga and Taubaté, for the South and East region of the state, Matão for the central region and Dracena fort the west region.

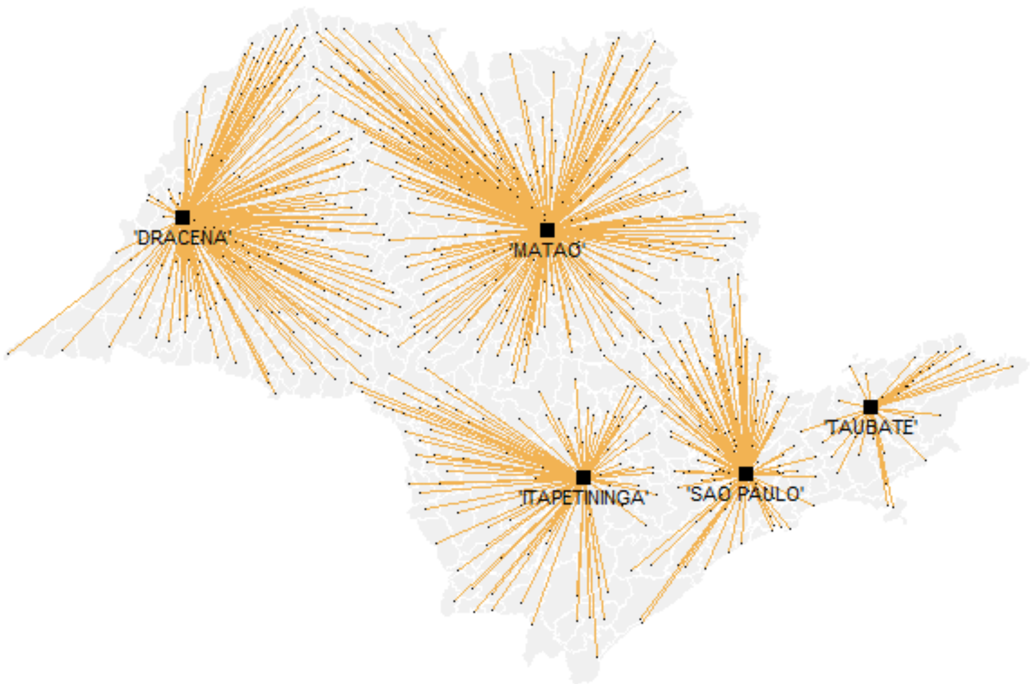

Figure 75 - Optimal disposition of the deposits according to the optimization model

The most part of the relief supplies demand is met by the São Paulo warehouse, 65%, reaching 66% of the population of the state, concentrated in 119 cities. São Paulo deposit consists also is responsible for about the 64% of the transportation costs.

The deposits of the “interior” of the state attend together only 21% of the demand also if in charge of meeting the demand of 61% of the cities of the state, counting 22% of the population of the state.

It is interesting to see that the warehouse in charge of meeting the cities of the Vale do Paraitinga, even if attending only 40 cities, and the 5% of the total population, is responsible for meeting the 15% of the total demand of relief supplies of the state. This highlights the high number of people living in a risk conditions in the area.

	MetCities	MetCities%	MetDem%	MetPop	MetPop%	WHVarCost
'SAO PAULO'	119	18%	65%	24214027	66%	145317
'DRACENA'	163	25%	5%	2344463	6%	13422
'ITAPETININGA'	94	15%	5%	2444161	7%	12146
'MATAO'	229	36%	9%	5797385	16%	23035
'TAUBATE'	40	6%	15%	2006467	5%	34405

Table 10 – Optimal warehouses configuration information

This solution indicates the best solution from a cost point of view, minimizing the cost of the installations.

Trasportation cost R$	228325
Stock management cost R$	20000
Annual depreciation R$	40000
Total cost R$	288325

Table 11 – Optimal warehouses disposition cost structure

This, anyways cause a trade off in terms of time to reach the demand points, anyway each demand point is reachable in less than 4 hours, in Figure 76 travel times smaller than 2 hours and an half are put on evidence (in green).

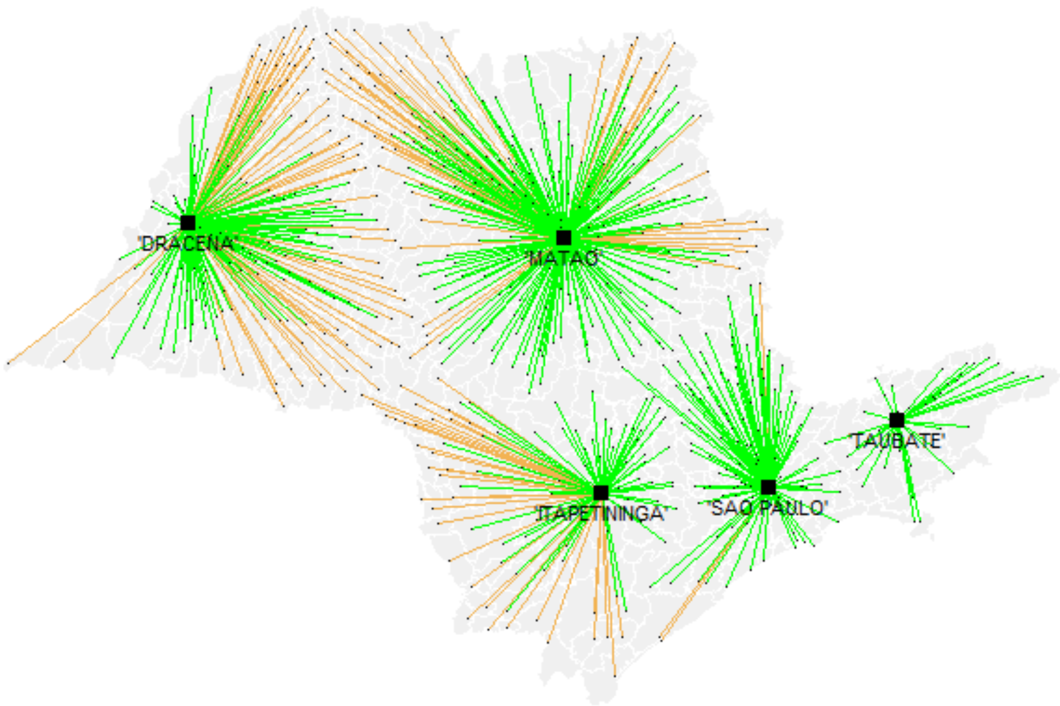

Figure 76 - Optimal solutions with travel times smaller than 150 minutes highlighted

7.1.1.2. Evaluation of the current warehouses disposition

The model has been also used to evaluate the current disposition of the warehouses. Is immediately evident looking at the results, that the deposits of Apiaí and Registro are responsible for meeting a very small percentage of the state demand for relief supplies. This tells us that the construction of a canvas warehouse in both those locations would be highly cost inefficient.

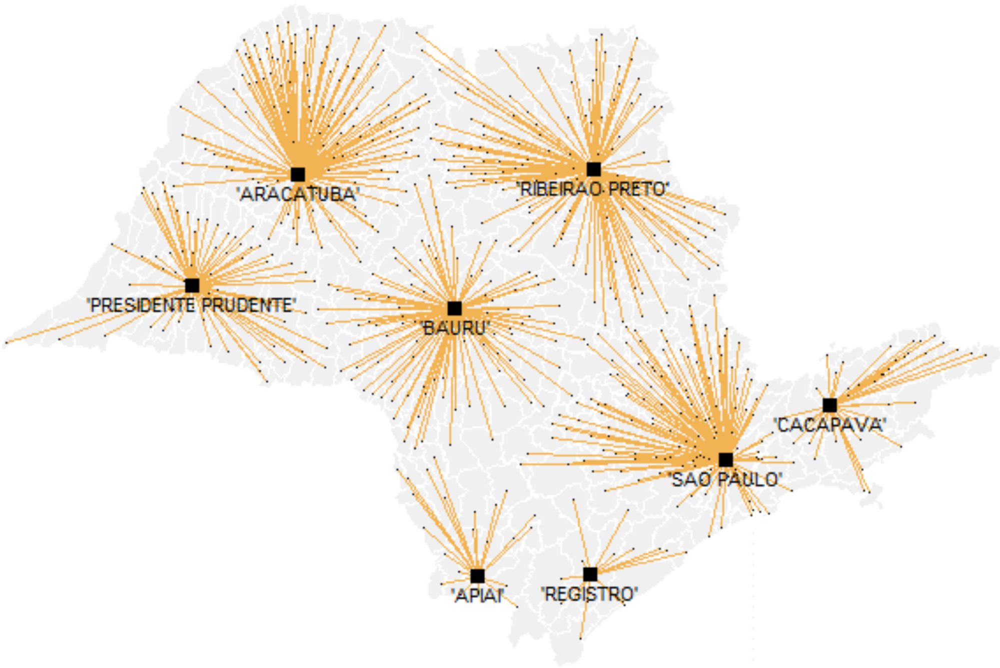

Figure 77 - Evaluation of the current warehouses disposition by means of the optimization model

	MetCities	MetCities%	MetDem%	MetPop	MetPop%	WHVarCost
'SAO PAULO'	139	22%	65%	25136000	68%	145962
'APIAI'	23	4%	1%	382937	1%	1840
'ARACATUBA'	127	20%	2%	1815569	5%	4378
'BAURU'	97	15%	5%	1990831	5%	12462
'CACAPAVA'	41	6%	15%	2028371	6%	35188
'PRESIDENTE PRUDENTE'	72	11%	3%	1130515	3%	7966
'REGISTRO'	16	2%	2%	348464	1%	5494
'RIBEIRAO PRETO'	130	20%	6%	3973816	11%	13452

Table 12 - Current warehouses configuration information

The high number of warehouses make this configuration inefficient from the point of view of stock management costs and installation costs.

Trasportation costs R$	226742
Stock management cost R$	32000
Annual depreciation R$	70000
Total cost R$	328742

Table 13 – Current warehouses disposition cost structure

In map can be seen that with this configuration the most part of the cities is reachable in less than 2 hours and an half. All the cities are reachable in less than 3 hours.

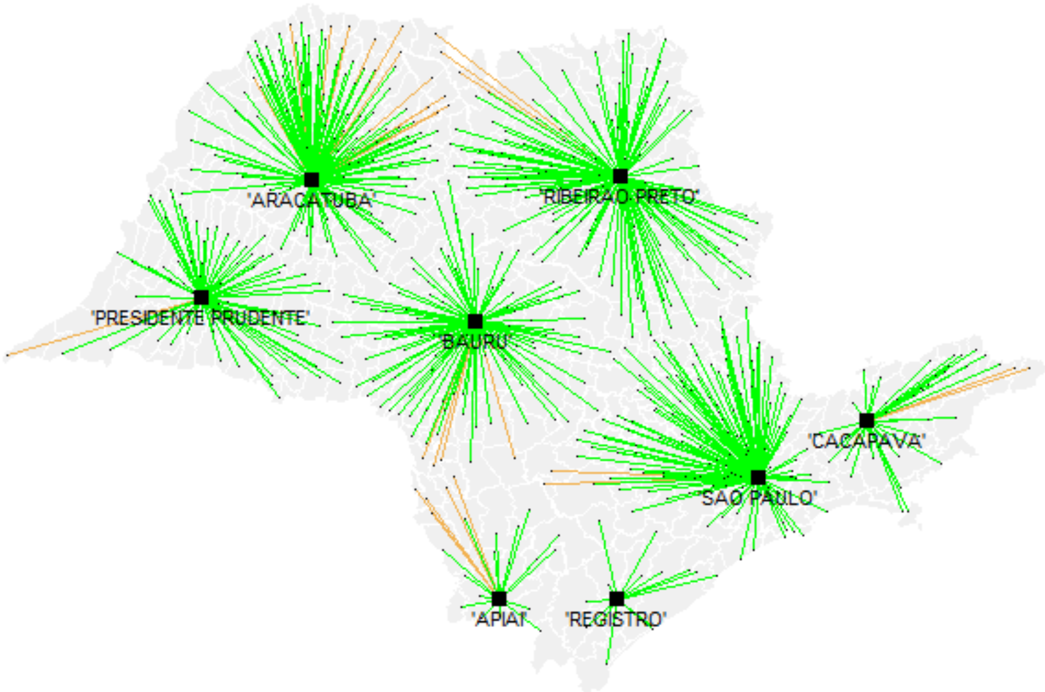

Figure 78 – Current warehouses configuration with travel times smaller than 150 minutes highlighted

Despite the low percentage of relief supplies demand attended from the warehouses of Apiaí and Registro, CEDEC affirmed that due bad road quality, in bad weather conditions it is very difficult to reach some areas of the Vale do Ribeira (region served by the two deposits), so the two deposits have and high strategic relevance.
This lead to evaluating the model forcing the opening of the two deposits.

7.1.1.3. Evaluation of the best solutions forcing the Apiaí and Registro deposits opening

Forcing the inclusion of the two cited deposits in the solution to the increase of the number of deposits in order to satisfy the constraint of travel time.

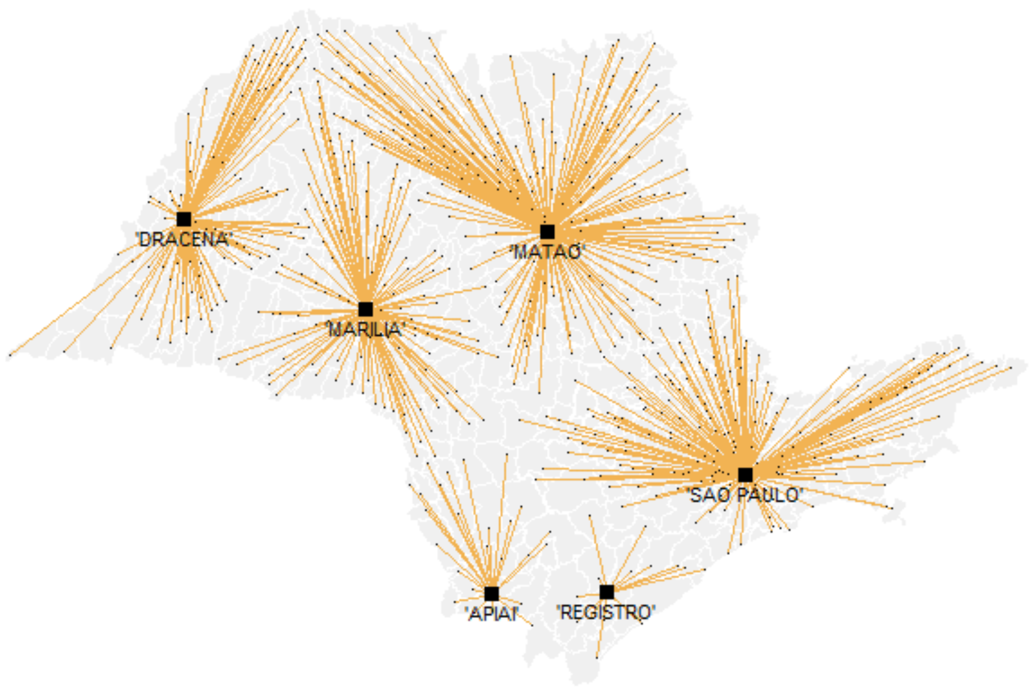

Figure 79 – Forced opening constrained optimal disposition of the deposits according to the optimization model

In this model, can be noticed that in order to reduce the total costs, the model chose to not open a warehouse in the region of the Vale do Paraiba, giving to the São Paulo deposit the duty to meet the demand of the region, bringing the demand in charge of the São Paulo deposit to the 81%. The time to attend the reach the cities of the region increased significantly.

	MetCities	MetCities%	MetDem%	MetPop	MetPop%	WHVarCost
'SAO PAULO'	188	29%	81%	27410549	74%	183966
'APIAI'	31	5%	1%	481667	1%	2659
'REGISTRO'	16	2%	2%	348464	1%	5494
'DRACENA'	164	25%	5%	2350164	6%	13426
'MATAO'	246	38%	10%	6215659	17%	24401

Table 14- Forced opening constrained warehouses configuration information

Trasportation costs R$	229947
Stock management cost R$	24000
Annual depreciation R$	50000
Total cost R$	303947

Table 15 –Forced opening constrained warehouses disposition cost structure

7.1.2. SOLUTION COMPARISON

Comparing the proposed solution can be seen that the actual configuration of warehouses is the one showing the best total transportation costs between the considered solutions, but the improvement with respect with the best solution proposed by the model, alone, is not high enough to justify the opening of the three deposits. This because the stock management costs considered in the models, alone, cause a growth in the costs of 12 000 R$. If we consider to install a canvas in each of the actual location the annual cost due to the depreciation will grow by 30 000 R$. For an increase of the total investment, over the 10 years, of 300 000 R$. Anyway, considering the relief supplies delivery time, there is an interesting improvement in the actual configuration with respect to the cost optimal solution.

7.1.3. CONSIDERATIONS ON THE SOLUTIONS TRESHOLDS

The minimum number of warehouses satisfying the delivery time limit is four. In this case, however, the mean delivery time is quite high.

If we consider a fixed number of warehouses equal to 16, thinking in installing a deposit in each REDEC, the model tells that his better to increase the concentration of deposit in the highly densely populated areas.

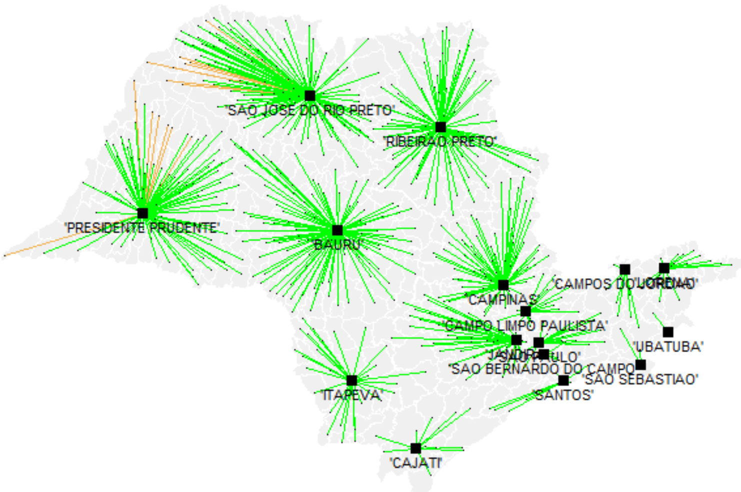

Figure 80 - 16 warehouses configuration

7.2. SUGGESTED ALTERNATIVE

Given the results obtained from the model described in the previous section, seems reasonable from an economic point of view to limit the number of installation of canvas warehouses to the minimum possible. This implies a trade-off with the delivery time, which for the cities farer from the warehouse location can be quite high, but according to the service used, still far from the imposed limit. However, the service used, does not considers possible adverse weather conditions that could increase the time needed to reach the city demanding for relief supplies.

A possible solution could be implementation of a mixed strategy between the one actually used, the use of existing facilities, and the one CEDEC wants to implement. This strategy consists in installing the canvas warehouses in strategic places, the one indicated as optimal solution from the model, for example, and using existing facilities as temporary deposits, with a limited capacity and quantity of stocked items, in charge to deal with disaster of small size, and with first support in case of bigger ones. An optimal solution in terms of cost would be to assign the management of the mini deposit to the volunteers of the COMDEC of the city where it should be located. This would bring the fixed cost to a minimum value, making the solution convenient.

Implementing this solution, Civil Defense logistic network would change as follows:

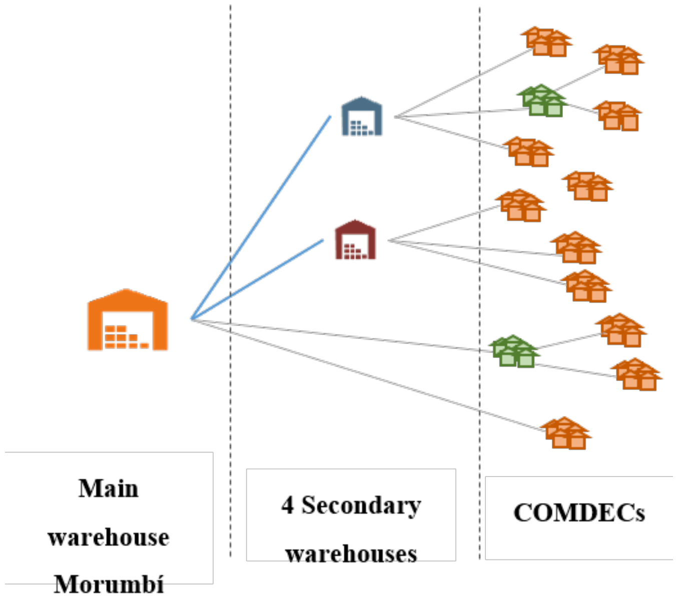

Figure 81 – New logistic network, in green highlighted the "mini-warehouses"

According to the results of the model, secondary warehouses should be located in the cities of Dracena, Matão, Itapetininga and Tabuaté, while would be interesting to have two "mini-warehouses", one of them located in the in the eastern part of the Vale do Ribeira, in Registro for example, and another in the far north of the state. This solution, however, has not been tested thought the model.

8. CONCLUSIONS

The work, developed in collaboration with São Paulo state Civil Defense, showed an overview of the number of people living in a condition of risk of the state of São Paulo and gave some interesting hints on how many disaster relief supplies warehouses should be installed and where.

To achieve this result an analyses and aggregation of the existing data was necessary, due to high fragmentation of the information.
The lack of available data imposed the use of regression models for count variables in order to have an estimate of the demand of relief supplies in case of disaster occurrence.
Successively a stochastic optimization model has been used to evaluate the 169 candidate locations in terms of cost and operational efficiency in the meeting of the estimated demand.

This work does not claim to offer a final answer to the question cited in the introduction of this monograph:
"In the São Paulo State, where should be located the relief supplies deposits for disaster response?"
It has to be intended instead, as the first brick of a more extended and complex work, that will lead to a more complete and exhaustive answer to the question.

The work will be presented to CEDEC and its results discussed with Civil Defense decision makers, in order to understand how to improve them, and in which directions the futures research on this field should point.

During its development, the work raised a series of interesting research challenges, as the development of the regression model linking the CEDEC historic of interventions with the number of people living in risk condition, which will be the trigger for further works.

9. FURTHER STUDIES

Several are the possibilities of researches that would bring improvement to the work, regarding both the regression models used to estimate the number of people living in risk conditions and the stochastic optimization model itself.

The regression model could be improved:

- Including other variables as historic of rains and urban area density of inhabitants.
- Including categorical variables describing the kind of the intervention or characteristics of the cities.
- Testing other regression methods for over dispersed and zero-inflated data .
- Including time in the regression models.
- Including disaster not included in the CEDEC historic, retrieved data mining old news.

The optimization model instead could be improved:

- Making sensitivity analyses on the model parameters, especially scenarios probability and warehouse installation cost.
- Obtaining more precise data about transportation cost, time and distance using professional services.
- Analyzing the location suggested in the best solutions of the model, in order to obtain more detailed data about the cost of installation of the warehouse.
- Considering a dynamic model, taking into account also the variable time.
- Including constraints on capacity.
- Including purchases and donations.
- Including ruptures.

Furthermore, analyzing the results of the model through multi criteria decision analyses could lead improve the final decision, taking into account qualitative aspects of difficult consideration in an optimization model.

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APPENDIX 1 - REDECS

Redec/I-01
Barra Do Turvo, Cajati, Cananéia, Eldorado, Iguape, Ilha Comprida, Itariri, Jacupiranga, Lavrinhas, Miracatu, Pariquera-Açu, Pedro De Toledo, Registro, Sete Barras

Redec/I-02
Bertioga, Cubatão, Guarujá, Itanhaém, Mongaguá, Peruíbe, Pratânia, Santos, São Vicente

Redec/I-03
Aparecida, Arapeí, Areias, Bananal, Caçapava, Cachoeira Paulista, Campos Do Jordão, Canas, Caraguatatuba, Cunha, Divinolândia, Guaratinguetá, Igaratá, Ilhabela, Jacareí, Jambeiro, Lagoinha, Lençóis Paulista, Lorena, Morungaba, Natividade Da Serra, Paraíbuna, Pindamonhangaba, Piraju, Pracinha, Rancharia, Redenção Da Serra, Roseira, Santa Ernestina, Santo Antônio Do Pinhal, São Bernardo Do Campo, São José Do Barreiro, São José Dos Campos, São Luíz Do Paraitinga, São Sebastião, Silveiras, Taubaté, Tremebé, Ubatuba

Redec/I-04
Águas De Santa Bárbara , Alambarí, Alumínio, Anhembi, Araçariguama, Araçoiaba Da Serra, Areiópolis, Avaré, Bofete, Boituva, Botucatu, Capela Do Alto, Cerqueira César, Cerquilho, Cesário Lange, Conchas, Guare , Iaras, Ibiúna, Iperó, Itapetininga, Itirapina, Itu, Jumirim, Laranjal Paulista, Mairinque, Maracaí, Patrocínio Paulista, Pereiras, Piedade, Pindorama, Porangaba, Porto Feliz, Presidente Bernardes, Quadra, Salto, Salto De Pirapora, São Miguel Arcanjo, São Pedro Do Turvo, São Roque, Serra Azul, Sorocaba, Tapiraí, Tatuí, Tietê, Torre De Pedra, Votorantim

Redec/I-05
Aguaí, Águas Da Prata, Águas De Lindóia, Águas De São Pedro, Americana, Amparo, Analândia, Araras, Arthur Nogueira, Atibaia, Bom Jesus Dos Perdões, Bragança Paulista, Brotas, Cabreúva, Caconde, Campinas, Campo Limpo Paulista, Capivari, Casa Branca, Charqueada, Cordeirópolis, Corumbataí, Cosmópolis, Cristais Paulista, Dois Córregos, Elias Fausto, Engenheiro Coelho, Espírito Santo Do Pinhal, Estiva Gerbi, Holambra, Hortolândia, Indaiatuba, Ipeúna, Iracemápolis, Itapira, Itatiba, Itobi, Itupeva, Jaboticabal, Jaguariúna, Jarinu, Jundiaí, Junqueirópolis, Leme, Limeira, Lindóia, Louveira, Mogi Mirim, Mogi-Guaçu, Mombuca, Monte Alegre Do Sul, Monte Aprazível, Monte Mor, Nazaré Paulista, Nova Aliança, Nova Odessa, Paulínia, Pedra Bela, Pedreira, Piquerobi, Piracaia, Piracicaba, Piratininga, Rafard, Rio Claro, Rio Das Pedras, Saltinho, Santa Bárbara D' Oeste, Santa Cruz Da Conceição , Santa Cruz Das Palmeiras, Santa Gertrudes, Santa Maria Da Serra, Santo Antonio De Posse, Santo Antonio Do Jardim, São João Do Pau D´Alho, São Manuel, São Pedro, Sarapuí, Serra Negra, Socorro, Sumaré, Tanabi, Tapiratiba, Torrinha, Tuiuti, Valinhos, Vargem, Várzea Paulista, Vera Cruz, Vinhedo

Redec/I-06
Altinópolis, Barrinha, Brodowski, Cajuru, Cássia Dos Coqueiros, Cravinhos, Dumont, Guatapará, Herculândia, Jales, Jardinópolis, Luís Antônio, Monte Alto, Pitangueiras, Pontal , Pradópolis, Ribeirão Preto, Santa Cruz Da Esperança , Santo Anastácio, Santo Antônio Da Alegria , São Simão, Serrana, Sertãozinho, Suzanópolis, Taquaral

Redec/I-07, Agudos, Arealva , Avaí, Balbinos, Bariri, Barra Bonita, Bauru, Bocaina, Boracéia, Borebi, Cabrália Paulista , Cafelândia, Dracena, Duartina, Getulina, Guaiçara, Guaimbê , Guarantã, Ibitinga, Igaraçu Do Tietê, Itaju, Itapura, Joanópolis, Lins, Lucélia, Lucianópolis, Macatuba, Mineiros Do Tietê, Paulistânia, Piacatu, Pirapozinho, Pompéia, Pontalinda, Presidente Alves, Quatá, Restinga, Santa Adélia, Ubirajara, Uru

Redec/I-08
Adolfo , Álvares Florence, Américo De Campos , Aparecida D´Oeste , Ariranha, Aspásia , Bady Bassit, Bálsamo , Cardoso , Catanduva, Catiguá , Cedral , Cosmorama, Dirce Reis, Dolcinópolis, Elisiário, Estrela D´Oeste , Flora Rica, Floreal , Guapiaçú, Guarani D´Oeste , Ibirá, Igarapava, Indiaporã, Ipiguá , Irapuã , Itajobi, Jaci, Jandira, José Bonifácio , Macaubal, Macedônia, Magda, Marapoama, Marinópolis, Mendonça, Meridiano, Mesópolis, Mira Estrela, Mirassolândia, Mococa, Monções , Monte Azul Paulista, Neves Paulista, Nhandeara, Nipoã, Nova Campina, Nova Canaã Paulista, Nova Independência, Novais , Olímpia, Onda Verde, Orindiúva, Ouroeste, Palestina, Palmeira D´Oeste, Panorama, Paraíso , Paranapuã, Parisi, Paulo De Faria , Pedranópolis, Pinhalzinho, Planalto, Poloni, Pontes Gestal, Populina, Potim, Potirendaba, Riolândia, Sabino, Sales, Santa Albertina , Santa Branca, Santa Clara D`Oeste, Santa Fé Do Sul , Santa Rita D´Oeste, Santa Salete, Santana Da Ponte Pensa, São Francisco, São João Das Duas Pontes, São José Do Rio Preto, Sebastianópolis Do Sul, Tabapuã , Tejupá, Três Fronteiras , Turmalina, Ubarana , Uchoa, União Paulista , Urânia , Valetim Gentil, Valparaíso, Vitória Brasil , Votuporanga, Zacarias

Redec/I-09

Alto Alegre, Andradina, Araçatuba, Auriflama, Avanhandava, Barbosa , Bento De Abreu, Bilac, Birigui, Braúna , Brejo Alegre, Buritama, Castilho, Clementina, Coroados, Gabriel Monteiro, Gastão Vidigal , Glicério, Guaíra, Guaraçaí, Guararapes, Guzolândia, Indiana, Itararé, Lavínia , Lourdes , Luiziânia, Mirante Do Paranapanema, Murutinga Do Sul, Nova Castilho, Nova Luzitânia , Novo Horizonte, Penápolis, Pereira Barreto , Pilar Do Sul, Rubiácea, Santópolis Do Aguapeí, São Bento Do Sapucaí, São João De Iracema, Sud Menucci, Taguaí, Turiúba , Vargem Grande Do Sul

Redec/I-10
Adamantina, Alfredo Marcondes, Álvares Machado, Anhumas , Caiabu, Caiuá, Embaúba, Emilianópolis, Estrela Do Norte, Fartura, Flórida Paulista, Florínea, Iepê, Inúbia Paulista, Ipuã, Itaí, Juquiá, Manduri, Marabá Paulista , Mariápolis, Mirandópolis, Mirassol, Monteiro Lobato, Nantes , Narandiba, Nova Guataporanga, Ouro Verde, Pacaembu, Palmares Paulista, Paraguaçu Paulista, Paulicéia, Piquete, Pirassunga, Praia Grande, Presidente Epitácio, Presidente Prudente, Presidente Venceslau, Promissão, Regente Feijó, Reginópolis, Ribeirão Pires, Rubinéia, Sagres , Salmourão, Sandovalina, Santa Mercedes , Santo Antônio Do Aracanguá, Santo Expedito , São José Do Rio Pardo, Taciba , Tarabaí , Tupã, Urupês

Redec/I-11
Álvaro De Carvalho , Alvinlândia, Arco Íris, Assis, Bastos, Bernardino De Campos, Borá,Campos Novos Paulista, Cândido Mota, Canitar, Chavantes, Colina, Cruzália, Echaporã, Espírito Santo Do Turvo, Fernão, Franca, Gália, Garça, Iacanga, Iacri, Ibirarema, Ipaussu, João Ramalho, Júlio Mesquita, Lupércio, Lutécia , Marília, Martinópolis, Ocauçu, Óleo, Oriente , Oscar Bressane, Ourinhos, Palmital, Paranapanema, Pardinho, Pedrinhas Paulista, Platina , Pongaí, Queiroz, Queluz, Quintana, Ribeirão Do Sul , Rinópolis, Salto Grande, Santa Cruz Do Rio Pardo, São Sebastião Da Grama, Tarumã, Timburi , Tupi Paulista,

Redec/I-12
Américo Brasiliense, Araraquara, Boa Esperança Do Sul, Borborema, Cândido Rodrigues, Descalvado, Dobrada , Dourado , Fernando Prestes, General Salgado, Ibaté, Icém, Itapuí, Matão, Motuca, Nova Granada, Porto Ferreira, Ribeirão Dos Índios, Rincão, Santa Lúcia, Santa Rita Do Passa Quatro, Santa Rosa Do Viterbo, São Carlos, Tabatinga, Taquaritinga, Trabiju

Redec/I-13
Altair, Barretos, Bebedouro, Cajobi , Colômbia, Conchal, Euclides Da Cunha Paulista, Guaraci , Guariba, Jaborandi, Monte Castelo, Orlândia, Pirangi , Severínia, Taiaçu, Taiúva, Terra Roxa, Viradouro, Vista Alegre Do Alto,
Redec/I-14, Aramina , Batatais, Buritizal, Cruzeiro, Gavião Peixoto, Guará, Ilha Solteira, Irapuru, Itirapuã, Ituverava, Jeriquara, Miguelópolis, Morro Agudo, Nuporanga, Osvaldo Cruz, Pederneiras, Pedregulho, Ribeirão Bonito, Ribeirão Corrente, Rifaina , Sales Oliveira, São Joaquim Da Barra, São José Da Bela Vista ,

Redec/I-15
Angatuba, Apiaí, Arandu , Barão De Antonina, Barra Do Chapéu, Bom Sucesso Do Itararé, Buri, Campina Do Monte Alegre, Capão Bonito, Coronel Macedo, Fernandópolis, Guapiara, Iporanga, Itaberá , Itaoca, Itapeva, Itapevi, Itapirapuã Paulista, Itaporanga, Itatinga, Nova Europa, Parapuã, Pirajuí, Ribeira, Ribeirão Branco, Ribeirao Grande, Rosana, Sarutaiá, Tambaú, Taquarituba, Taquarivaí, Teodoro Sampaio

Redec/M-1
São Paulo

Redec/M-2
Diadema, Mauá, Rio Grande Da Serra, Riversul, Santo André, São Caetano Do Sul, São João Da Boa Vista

Redec/M-3
Arujá, Biritiba Mirim, Caieiras, Ferraz De Vasconcelos, Francisco Morato, Franco Da Rocha, Guararema, Guarulhos, Itaquaquecetuba, Mairiporã, Mogi Das Cruzes, Poá, Salesópolis, Santa Isabel, Suzano

Redec/M-4
Barueri, Cajamar, Carapicuíba, Cotia, Embu Das Artes, Embu-Guaçu, Itapecerica Da Serra, Itápolis, Jaú, Juquitiba, Osasco, Pirapora Do Bom Jesus, Santana De Parnaíba, São Lourenço Da Serra, Taboão Da Serra, Vargem Grande Paulista

APPENDIX 2 - KIT COMPOSITION

- Bedding Kit: 1 bedding, 1 sheet, 1 blanket, 1 pillow, 1 pillowcase
- Cleaning Kit: 1 bottle of DHW, 1 bucket, 1 sponge, 2 pairs of gloves, 1 dustpan, 1 cleaning cloth, 1 squeegee, 2 soap bricks, 4 garbage
- Dressing Kit: 1 sweater, 1 t-shirt, 1 pair shoes
- Hygiene Kit: 2 units of toothpaste, 2 units of hand soap, 4 toothbrushes, 4 bath towels

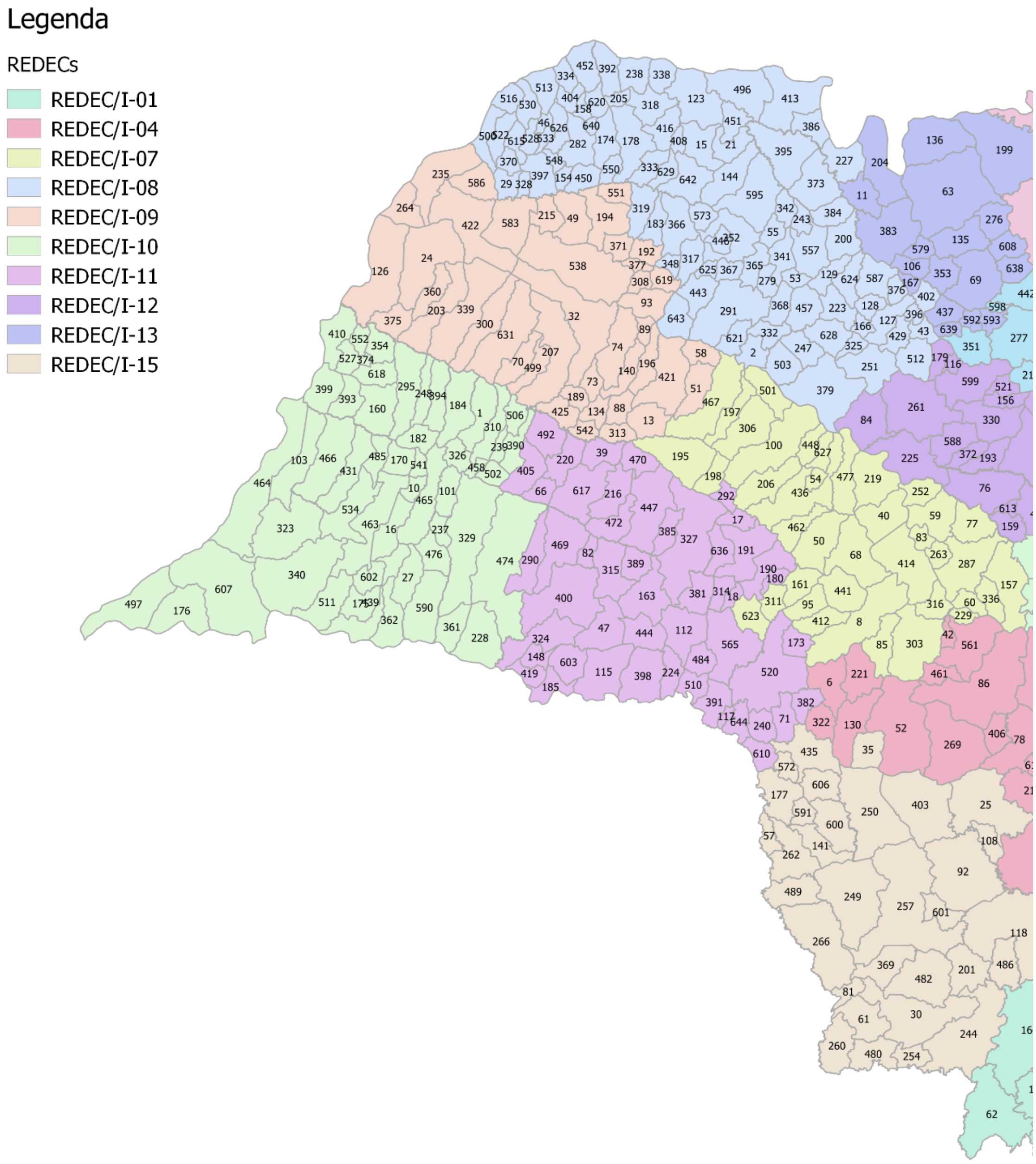
APPENDIX 3 - CANDIDATE LOCATIONS

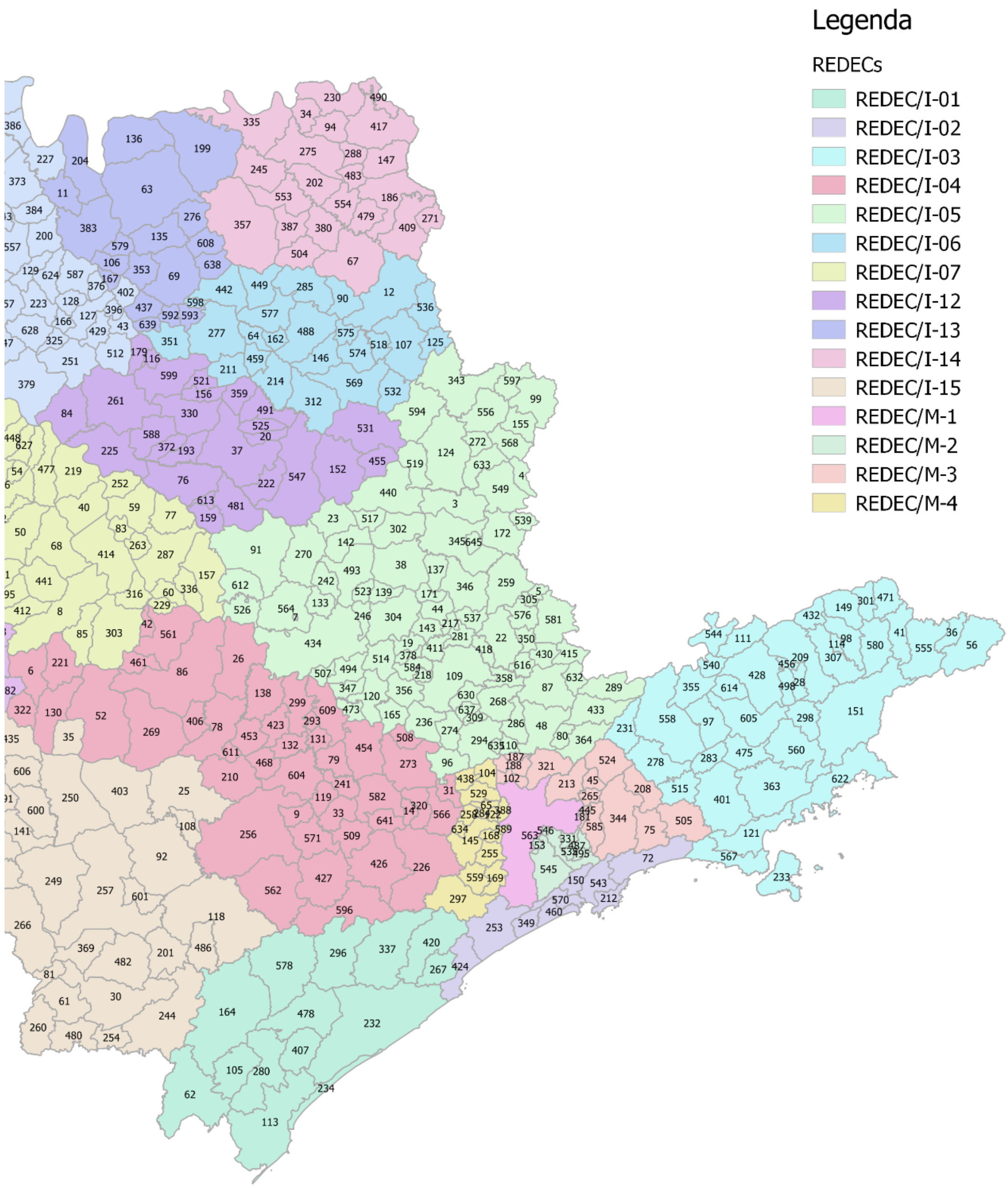
1. ADAMANTINA
2. AGUAÍ
3. AGUDOS
4. AMERICANA
5. AMÉRICO BRASILIENSE
6. AMPARO
7. ANDRADINA
8. APARECIDA
9. APIAÍ
10. ARAÇATUBA
11. ARARAQUARA
12. ARARAS
13. ARTHUR NOGUEIRA
14. ASSIS
15. ATIBAIA
16. AVARÉ
17. BARIRI
18. BARRA BONITA
19. BARRETOS
20. BATATAIS
21. BAURU
22. BEBEDOURO
23. BERTIOGA
24. BIRIGUI
25. BOITUVA
26. BOTUCATU
27. BRAGANÇA PAULISTA
28. CABREÚVA
29. CAÇAPAVA
30. CACHOEIRA PAULISTA
31. CAJATI
32. CAMPINAS
33. CAMPO LIMPO PAULISTA
34. CAMPOS DO JORDÃO
35. CÂNDIDO MOTA
36. CAPÃO BONITO
37. CAPIVARI
38. CARAGUATATUBA
39. CASA BRANCA
40. CATANDUVA
41. CERQUILHO
42. COSMÓPOLIS
43. CRAVINHOS
44. CRUZEIRO
45. CUBATÃO
46. DESCALVADO
47. DRACENA
48. ESPÍRITO SANTO DO PINHAL
49. FERNANDÓPOLIS
50. FRANCA
51. GARÇA
52. GUAÍRA
53. GUARARAPES
54. GUARATINGUETÁ
55. GUARIBA
56. GUARUJÁ
57. HORTOLÂNDIA
58. IBATÉ
59. IBITINGA
60. IBIÚNA
61. IGARAPAVA
62. IGUAPE
63. INDAIATUBA
64. ITANHAÉM
65. ITAPETININGA
66. ITAPEVA
67. ITAPEVI
68. ITAPIRA
69. ITARARÉ
70. ITATIBA
71. ITU
72. ITUPEVA
73. ITUVERAVA
74. JABOTICABAL
75. JACAREÍ
76. JAGUARIÚNA
77. JALES
78. JANDIRA
79. JARDINÓPOLIS
80. JOSÉ BONIFÁCIO
81. JUNDIAÍ
82. LEME
83. LENÇÓIS PAULISTA
84. LIMEIRA
85. LINS
86. LORENA
87. MAIRINQUE
88. MARÍLIA
89. MATÃO
90. MIRANDÓPOLIS
91. MIRASSOL
92. MOCOCA
93. MOGI-GUAÇU
94. MOGI MIRIM
95. MONGAGUÁ
96. MONTE ALTO
97. MONTE MOR
98. MORRO AGUDO
99. NOVA ODESSA
100. NOVO HORIZONTE
101. OLÍMPIA
102. ORLÂNDIA
103. OSVALDO CRUZ
104. OURINHOS
105. PARAGUAÇU PAULISTA
106. PAULÍNIA
107. PEDERNEIRAS
108. PEDREIRA
109. PENÁPOLIS
110. PEREIRA BARRETO
111. PERUÍBE
112. PIEDADE
113. PINDAMONHANGA BA
114. PIRACICABA
115. PIRAJU
116. PIRASSUNGA
117. PITANGUEIRAS
118. PONTAL
119. PORTO FELIZ
120. PORTO FERREIRA
121. PRAIA GRANDE
122. PRESIDENTE EPITÁCIO
123. PRESIDENTE PRUDENTE
124. PRESIDENTE VENCESLAU
125. PROMISSÃO
126. RANCHARIA
127. REGISTRO
128. RIBEIRÃO PIRES
129. RIBEIRÃO PRETO
130. RIO CLARO
131. SALTO
132. SALTO DE PIRAPORA
133. SANTA BÁRBARA D OESTE
134. SANTA CRUZ DAS PALMEIRAS
135. SANTA CRUZ DO RIO PARDO
136. SANTA FÉ DO SUL
137. SANTA RITA DO PASSA QUATRO
138. SANTOS
139. SÃO BERNARDO DO CAMPO
140. SÃO CARLOS

141. SÃO JOAQUIM DA BARRA
142. SÃO JOSÉ DO RIO PARDO
143. SÃO JOSÉ DO RIO PRETO
144. SÃO JOSÉ DOS CAMPOS
145. SÃO MANUEL
146. SÃO MIGUEL ARCANJO
147. SÃO PAULO
148. SÃO PEDRO
149. SÃO ROQUE
150. SÃO SEBASTIÃO
151. SÃO VICENTE
152. SERRANA
153. SERTÃOZINHO
154. SOCORRO
155. SOROCABA
156. SUMARÉ
157. TAQUARITINGA
158. TATUÍ
159. TAUBATÉ
160. TIETÊ
161. TREMEMBÉ
162. TUPÃ
163. UBATUBA
164. VALINHOS
165. VARGEM GRANDE DO SUL
166. VÁRZEA PAULISTA
167. VINHEDO
168. VOTORANTIM
169. VOTUPORANGA

APPENDIX 4 - MAP AND INDEXES

Map of the state with identifier




Legenda
REDECs
REDEC/I-01
REDEC/I-02
REDEC/I-03
REDEC/I-04
REDEC/I-05
REDEC/I-06
REDEC/I-07
REDEC/I-12
REDEC/I-13
REDEC/I-14
REDEC/I-15
REDEC/M-1
REDEC/M-2
REDEC/M-3
REDEC/M-4

APPENDIX 5 - PEOPLE AT RISK

Map Num	IBGE GEOCO	REDEC	City name	Pop	Source	Year	R1	R2	R3	R4
1	3500105	I-10	ADAMANTINA	33497	EST	2015	41	75	116	36
2	3500204	I-08	ADOLFO	3684	NO RISK	2015	0	0	0	0
3	3500303	I-05	AGUAÍ	28195	NO RISK	2015	0	0	0	0
4	3500402	I-05	ÁGUAS DA PRATA	7131	EST	2015	7	14	20	4
5	3500501	I-05	ÁGUAS DE LINDÓIA	16190	CPRM	2013	0	0	722	400
6	3500550	I-04	ÁGUAS DE SANTA BÁRBARA	5224	NO RISK	2015	0	0	0	0
7	3500600	I-05	ÁGUAS DE SÃO PEDRO	1883	NO RISK	2015	0	0	0	0
8	3500709	I-07	AGUDOS	32484	EST	2015	50	89	92	35
9	3500758	I-04	ALAMBARÍ	3650	NO RISK	2015	0	0	0	0
10	3500808	I-10	ALFREDO MARCONDES	3697	EST	2015	5	9	10	2
11	3500907	I-13	ALTAIR	3530	NO RISK	2015	0	0	0	0
12	3501004	I-06	ALTINÓPOLIS	15481	NO RISK	2015	0	0	0	0
13	3501103	I-09	ALTO ALEGRE	4261	NO RISK	2015	0	0	0	0
14	3501152	I-04	ALUMÍNIO	15252	IG/CEDEC	2005	185	75	30	6
15	3501202	I-08	ÁLVARES FLORENCE	4316	EST	2015	9	15	12	3
16	3501301	I-10	ÁLVARES MACHADO	22661	EST	2015	34	60	69	14
17	3501400	I-11	ÁLVARO DE CARVALHO	4109	NO RISK	2015	0	0	0	0
18	3501509	I-11	ALVINLÂNDIA	2837	NO RISK	2015	0	0	0	0
19	3501608	I-05	AMERICANA	182593	IPT/CEDEC	2013	0	0	33	0
20	3501707	I-12	AMÉRICO BRASILIENSE	28287	EST	2015	30	58	80	17
21	3501806	I-08	AMÉRICO DE CAMPOS	5594	NO RISK	2015	0	0	0	0
22	3501905	I-05	AMPARO	60404	EST	2015	135	182	314	151
23	3502002	I-05	ANALÂNDIA	3582	CPRM/CEDEC	2015	0	0	6	0
24	3502101	I-09	ANDRADINA	55161	NO RISK	2015	0	0	0	0
25	3502200	I-15	ANGATUBA	19297	NO RISK	2015	0	0	0	0
26	3502309	I-04	ANHEMBI	4535	EST	2015	8	13	13	3
27	3502408	I-10	ANHUMAS	3411	NO RISK	2015	0	0	0	0
28	3502507	I-03	APARECIDA	34904	IG/CEDEC	2012	1109	325	202	140
29	3502606	I-08	APARECIDA D´OESTE	4935	NO RISK	2015	0	0	0	0
30	3502705	I-15	APIAÍ	27162	CBH-RB	2011	0	0	0	46
31	3502754	I-04	ARAÇARIGUAMA	11154	IPT/CEDEC	2004	17	41	13	0
32	3502804	I-09	ARAÇATUBA	169254	IPT/CEDEC	2015	0	30	0	0
33	3502903	I-04	ARAÇOIABA DA SERRA	19816	NO RISK	2015	0	0	0	0
34	3503000	I-14	ARAMINA	4763	NO RISK	2015	0	0	0	0
35	3503109	I-15	ARANDU	6065	NO RISK	2015	0	0	0	0
36	3503158	I-03	ARAPEÍ	2618	IPT/CEDEC	2014	0	35	0	0
37	3503208	I-12	ARARAQUARA	182471	IG/CEDEC	2008	0	3	0	0
38	3503307	I-05	ARARAS	104196	IPT/CEDEC	2015	3	7	0	0
39	3503356	I-11	ARCO ÍRIS	2163	NO RISK	2015	0	0	0	0
40	3503406	I-07	AREALVA	7244	NO RISK	2015	0	0	0	0
41	3503505	I-03	AREIAS	3600	IPT/CEDEC	2013	0	10	40	0
42	3503604	I-04	AREIÓPOLIS	10296	EST	2015	24	40	29	6
43	3503703	I-08	ARIRANHA	7477	EST	2015	10	18	23	5
44	3503802	I-05	ARTHUR NOGUEIRA	33124	CPRM	2014	0	0	19	0
45	3503901	M-3	ARUJÁ	59185	EST	2015	73	135	180	59
46	3503950	I-08	ASPÁSIA	1861	NO RISK	2015	0	0	0	0
47	3504008	I-11	ASSIS	87251	EST	2015	84	158	317	53
48	3504107	I-05	ATIBAIA	111300	CPRM	2012	0	0	354	1264
49	3504206	I-09	AURIFLAMA	13513	EST	2015	15	28	41	8
50	3504305	I-07	AVAÍ	4596	NO RISK	2015	0	0	0	0
51	3504404	I-09	AVANHANDAVA	8829	NO RISK	2015	0	0	0	0
52	3504503	I-04	AVARÉ	76472	EST	2015	85	154	283	74
53	3504602	I-08	BADY BASSIT	11550	NO RISK	2015	0	0	0	0
54	3504701	I-07	BALBINOS	1313	NO RISK	2015	0	0	0	0
55	3504800	I-08	BÁLSAMO	7340	NO RISK	2015	0	0	0	0
56	3504909	I-03	BANANAL	9713	IPT/CEDEC	2013	0	28	142	16
57	3505005	I-15	BARÃO DE ANTONINA	2794	NO RISK	2015	0	0	0	0
58	3505104	I-09	BARBOSA	5837	NO RISK	2015	0	0	0	0
59	3505203	I-07	BARIRI	28224	EST	2015	32	61	80	17
60	3505302	I-07	BARRA BONITA	35487	NO RISK	2015	0	0	0	0
61	3505351	I-15	BARRA DO CHAPÉU	4846	CBH-RB	2011	0	0	34	0
62	3505401	I-01	BARRA DO TURVO	8108	CBH-RB	2011	260	0	70	5
63	3505500	I-13	BARRETOS	103913	IPT/CEDEC	2015	0	124	0	0
64	3505609	I-06	BARRINHA	24207	EST	2015	37	66	68	15
65	3505708	M-4	BARUERI	208281	EST	2015	216	387	886	455
66	3505807	I-11	BASTOS	20588	NO RISK	2015	0	0	0	0
67	3505906	I-14	BATATAIS	51112	EST	2015	49	95	156	31
68	3506003	I-07	BAURU	316064	EST	2015	332	567	1481	387
69	3506102	I-13	BEBEDOURO	74815	IG/CEDEC	2008	0	40	0	0

Map Num	IBGE GEOCO	REDEC	City name	Pop	Source	Year	R1	R2	R3	R4
70	3506201	I-09	BENTO DE ABREU	2394	EST	2015	3	6	7	1
71	3506300	I-11	BERNARDINO DE CAMPOS	10720	EST	2015	20	33	31	7
72	3506359	I-02	BERTIOGA	30039	IPT/CEDEC	2014	0	0	1743	0
73	3506409	I-09	BILAC	6088	NO RISK	2015	0	0	0	0
74	3506508	I-09	BIRIGUI	94300	EST	2015	106	200	287	58
75	3506607	M-3	BIRITIBA MIRIM	24653	IPT/CEDEC	2013	0	63	10	10
76	3506706	I-12	BOA ESPERANÇA DO SUL	12573	EST	2015	28	47	36	8
77	3506805	I-07	BOCAINA	9442	EST	2015	11	21	29	6
78	3506904	I-04	BOFETE	7356	EST	2015	15	24	26	16
79	3507001	I-04	BOITUVA	34368	IPT/CEDEC	2015	0	103	0	0
80	3507100	I-05	BOM JESUS DOS PERDÕES	13313	EST	2015	23	40	41	20
81	3507159	I-15	BOM SUCESSO DO ITARARÉ	3231	NO RISK	2015	0	0	0	0
82	3507209	I-11	BORÁ	795	NO RISK	2015	0	0	0	0
83	3507308	I-07	BORACÉIA	3739	NO RISK	2015	0	0	0	0
84	3507407	I-12	BORBOREMA	13193	NO RISK	2015	0	0	0	0
85	3507456	I-07	BOREBI	1933	NO RISK	2015	0	0	0	0
86	3507506	I-04	BOTUCATU	108306	IPT/CEDEC	2015	0	15	28	0
87	3507605	I-05	BRAGANÇA PAULISTA	125031	CPRM	2012	0	0	282	260
88	3507704	I-09	BRAÚNA	4383	NO RISK	2015	0	0	0	0
89	3507753	I-09	BREJO ALEGRE	2308	NO RISK	2015	0	0	0	0
90	3507803	I-06	BRODOWSKI	17139	NO RISK	2015	0	0	0	0
91	3507902	I-05	BROTAS	18886	EST	2015	21	39	53	12
92	3508009	I-15	BURI	17629	EST	2015	61	92	51	11
93	3508108	I-09	BURITAMA	13854	NO RISK	2015	0	0	0	0
94	3508207	I-14	BURITIZAL	3674	NO RISK	2015	0	0	0	0
95	3508306	I-07	CABRÁLIA PAULISTA	4656	NO RISK	2015	0	0	0	0
96	3508405	I-05	CABREÚVA	33100	CPRM	2013	0	0	68	0
97	3508504	I-03	CAÇAPAVA	76130	IG/CEDEC	2012	300	78	1	170
98	3508603	I-03	CACHOEIRA PAULISTA	27205	IPT/CEDEC	2014	0	73	597	0
99	3508702	I-05	CACONDE	18378	EST	2015	47	71	60	11
100	3508801	I-07	CAFELÂNDIA	15793	EST	2015	28	49	45	10
101	3508900	I-10	CAIABU	4077	EST	2015	9	15	12	2
102	3509007	M-3	CAIEIRAS	71221	IPT/CEDEC	2005	0	278	313	42
103	3509106	I-10	CAIUÁ	4192	EST	2015	21	30	12	3
104	3509205	M-4	CAJAMAR	50761	IPT/CEDEC	2006	140	323	404	93
105	3509254	I-01	CAJATI	29227	CBH-RB	2011	163	132	517	140
106	3509304	I-13	CAJOBI	9174	NO RISK	2015	0	0	0	0
107	3509403	I-06	CAJURU	20777	EST	2015	32	57	59	13
108	3509452	I-15	CAMPINA DO MONTE ALEGRE	5209	EST	2015	12	20	15	3
109	3509502	I-05	CAMPINAS	969396	CPRM	2013	0	0	2750	0
110	3509601	I-05	CAMPO LIMPO PAULISTA	63724	EST	2015	103	171	256	216
111	3509700	I-03	CAMPOS DO JORDÃO	44252	IG/CEDEC	2014	608	1140	907	1331
112	3509809	I-11	CAMPOS NOVOS PAULISTA	4181	NO RISK	2015	0	0	0	0
113	3509908	I-01	CANANÉIA	12298	EST	2015	29	45	48	19
114	3509957	I-03	CANAS	3614	IPT/CEDEC	2014	0	73	0	0
115	3510005	I-11	CÂNDIDO MOTA	29280	NO RISK	2015	0	0	0	0
116	3510104	I-12	CÂNDIDO RODRIGUES	2613	EST	2015	4	8	7	30
117	3510153	I-11	CANITAR	3481	NO RISK	2015	0	0	0	0
118	3510203	I-15	CAPÃO BONITO	46732	EST	2015	147	230	132	29
119	3510302	I-04	CAPELA DO ALTO	14247	IPT/CEDEC	2015	0	7	0	0
120	3510401	I-05	CAPIVARI	41468	IPT/CEDEC	2014	0	78	250	0
121	3510500	I-03	CARAGUATATUBA	78921	EST	2015	183	255	393	236
122	3510609	M-4	CARAPICUÍBA	344596	CPRM	2012	0	0	1325	250
123	3510708	I-08	CARDOSO	11605	NO RISK	2015	0	0	0	0
124	3510807	I-05	CASA BRANCA	26800	NO RISK	2015	0	0	0	0
125	3510906	I-06	CÁSSIA DOS COQUEIROS	2871	NO RISK	2015	0	0	0	0
126	3511003	I-09	CASTILHO	14948	EST	2015	25	44	42	9
127	3511102	I-08	CATANDUVA	105847	EST	2015	78	160	299	65
128	3511201	I-08	CATIGUÁ	6555	NO RISK	2015	0	0	0	0
129	3511300	I-08	CEDRAL	6700	NO RISK	2015	0	0	0	0
130	3511409	I-04	CERQUEIRA CÉSAR	15144	EST	2015	28	47	46	21
131	3511508	I-04	CERQUILHO	29508	NO RISK	2015	0	0	0	0
132	3511607	I-04	CESÁRIO LANGE	12883	CPRM/CEDEC	2015	0	0	9	0
133	3511706	I-05	CHARQUEADA	13037	CPRM/CEDEC	2015	0	0	57	1
134	3511904	I-09	CLEMENTINA	5404	NO RISK	2015	0	0	0	0
135	3512001	I-11	COLINA	16664	EST	2015	21	39	47	10
136	3512100	I-13	COLÔMBIA	5954	NO RISK	2015	0	0	0	0
137	3512209	I-13	CONCHAL	22676	EST	2015	43	73	64	14
138	3512308	I-04	CONCHAS	14904	CPRM/CEDEC	2015	0	0	98	0
139	3512407	I-05	CORDEIRÓPOLIS	17591	CPRM/CEDEC	2015	0	0	85	0
140	3512506	I-09	COROADOS	4417	NO RISK	2015	0	0	0	0

Map Num	IBGE GEOCO	REDEC	City name	Pop	Source	Year	R1	R2	R3	R4
141	3512605	I-15	CORONEL MACEDO	5589	NO RISK	2015	0	0	0	0
142	3512704	I-05	CORUMBATAÍ	3794	NO RISK	2015	0	0	0	0
143	3512803	I-05	COSMÓPOLIS	44355	IPT/CEDEC	2014	0	450	54	0
144	3512902	I-08	COSMORAMA	7372	NO RISK	2015	0	0	0	0
145	3513009	M-4	COTIA	148987	IG/CEDEC	2006	27	308	1489	966
146	3513108	I-06	CRAVINHOS	28411	NO RISK	2015	0	0	0	0
147	3513207	I-05	CRISTAIS PAULISTA	6579	EST	2015	14	23	19	4
148	3513306	I-11	CRUZÁLIA	2610	NO RISK	2015	0	0	0	0
149	3513405	I-14	CRUZEIRO	73492	EST	2015	130	194	359	137
150	3513504	I-02	CUBATÃO	108309	FUNESP	2006	0	513	493	100
151	3513603	I-03	CUNHA	23090	BRITO	2014	0	0	97	529
152	3513702	I-12	DESCALVADO	28921	NO RISK	2015	0	0	0	0
153	3513801	M-2	DIADEMA	357064	IG/CEDEC	2005	868	730	335	0
154	3513850	I-08	DIRCE REIS	1623	NO RISK	2015	0	0	0	0
155	3513900	I-03	DIVINOLÂNDIA	12016	EST	2015	23	38	38	7
156	3514007	I-12	DOBRADA	7007	NO RISK	2015	0	0	0	0
157	3514106	I-05	DOIS CÓRREGOS	22522	EST	2015	29	54	64	14
158	3514205	I-08	DOLCINÓPOLIS	2152	NO RISK	2015	0	0	0	0
159	3514304	I-12	DOURADO	8606	NO RISK	2015	0	0	0	0
160	3514403	I-07	DRACENA	40500	EST	2015	66	108	125	25
161	3514502	I-07	DUARTINA	12475	NO RISK	2015	0	0	0	0
162	3514601	I-06	DUMONT	6307	NO RISK	2015	0	0	0	0
163	3514700	I-11	ECHAPORÃ	6827	NO RISK	2015	0	0	0	0
164	3514809	I-01	ELDORADO	14134	CBH-RB	2011	177	360	91	227
165	3514908	I-05	ELIAS FAUSTO	13888	IPT/CEDEC	2015	0	11	0	0
166	3514924	I-08	ELISIÁRIO	2577	NO RISK	2015	0	0	0	0
167	3514957	I-10	EMBAÚBA	2478	EST	2015	3	6	7	2
168	3515004	M-4	EMBU DAS ARTES	207663	PREF-EMBU	2004	13	311	768	623
169	3515103	M-4	EMBU-GUAÇU	56916	CPRM	2012	0	0	474	5
170	3515129	I-10	EMILIANÓPOLIS	2893	NO RISK	2015	0	0	0	0
171	3515152	I-05	ENGENHEIRO COELHO	10033	IPT/CEDEC	2012	0	0	1	0
172	3515186	I-05	ESPÍRITO SANTO DO PINHAL	40480	CPRM/CEDEC	2015	0	0	542	0
173	3515194	I-11	ESPÍRITO SANTO DO TURVO	3677	NO RISK	2015	0	0	0	0
174	3515202	I-08	ESTRELA D´OESTE	8256	NO RISK	2015	0	0	0	0
175	3515301	I-10	ESTRELA DO NORTE	2625	NO RISK	2015	0	0	0	0
176	3515350	I-13	EUCLIDES DA CUNHA PAULISTA	10214	EST	2015	26	42	29	6
177	3515400	I-10	FARTURA	15010	EST	2015	33	55	43	9
178	3515509	I-15	FERNANDÓPOLIS	61647	EST	2015	57	109	213	38
179	3515608	I-12	FERNANDO PRESTES	5434	IG/CEDEC	2008	0	0	0	24
180	3515657	I-11	FERNÃO	1432	NO RISK	2015	0	0	0	0
181	3515707	M-3	FERRAZ DE VASCONCELOS	142377	IPT/CEDEC	2013	0	410	458	767
182	3515806	I-08	FLORA RICA	2177	EST	2015	5	9	7	1
183	3515905	I-08	FLOREAL	3223	NO RISK	2015	0	0	0	0
184	3516002	I-10	FLÓRIDA PAULISTA	11106	EST	2015	22	37	31	7
185	3516101	I-10	FLORÍNEA	3127	EST	2015	5	9	9	2
186	3516200	I-11	FRANCA	287737	EST	2015	386	601	1409	176
187	3516309	M-3	FRANCISCO MORATO	133738	IPT/CEDEC	2005	50	546	377	1350
188	3516408	M-3	FRANCO DA ROCHA	108122	IG/CEDEC	2006	267	1732	2395	700
189	3516507	I-09	GABRIEL MONTEIRO	2726	NO RISK	2015	0	0	0	0
190	3516606	I-11	GÁLIA	7853	NO RISK	2015	0	0	0	0
191	3516705	I-11	GARÇA	43162	NO RISK	2015	0	0	0	0
192	3516804	I-09	GASTÃO VIDIGAL	3586	NO RISK	2015	0	0	0	0
193	3516853	I-14	GAVIÃO PEIXOTO	4126	EST	2015	6	11	12	3
194	3516903	I-12	GENERAL SALGADO	10824	EST	2015	15	28	31	7
195	3517000	I-07	GETULINA	10370	IPT/CEDEC	2015	0	10	5	0
196	3517109	I-09	GLICÉRIO	4428	NO RISK	2015	0	0	0	0
197	3517208	I-07	GUAIÇARA	9211	NO RISK	2015	0	0	0	0
198	3517307	I-07	GUAIMBÊ	5207	NO RISK	2015	0	0	0	0
199	3517406	I-09	GUAÍRA	34610	EST	2015	50	90	98	21
200	3517505	I-08	GUAPIAÇÚ	14086	NO RISK	2015	0	0	0	0
201	3517604	I-15	GUAPIARA	19726	NO RISK	2015	0	0	0	0
202	3517703	I-14	GUARÁ	18916	NO RISK	2015	0	0	0	0
203	3517802	I-09	GUARAÇAÍ	8894	NO RISK	2015	0	0	0	0
204	3517901	I-13	GUARACI	8846	NO RISK	2015	0	0	0	0
205	3518008	I-08	GUARANI D´OESTE	2006	NO RISK	2015	0	0	0	0
206	3518107	I-07	GUARANTÃ	6323	NO RISK	2015	0	0	0	0
207	3518206	I-09	GUARARAPES	28843	NO RISK	2015	0	0	0	0
208	3518305	M-3	GUARAREMA	21904	CPRM	2012	0	0	92	261
209	3518404	I-03	GUARATINGUETÁ	104219	BRITO	2014	941	848	561	431
210	3518503	I-04	GUAREÍ	10197	NO RISK	2015	0	0	0	0
211	3518602	I-13	GUARIBA	31085	EST	2015	61	102	102	19
212	3518701	I-02	GUARUJÁ	264812	IPT	2007	1903	1037	763	538

Map Num	IBGE GEOCO	REDEC	City name	Pop	Source	Year	R1	R2	R3	R4
213	3518800	M-3	GUARULHOS	1072717	PREF-GUA	2004	0	0	758	829
214	3518859	I-06	GUATAPARÁ	6371	NO RISK	2015	0	0	0	0
215	3518909	I-09	GUZOLÂNDIA	4295	NO RISK	2015	0	0	0	0
216	3519006	I-06	HERCULÂNDIA	7992	EST	2015	20	32	23	5
217	3519055	I-05	HOLAMBRA	7211	IPT/CEDEC	2012	0	0	25	0
218	3519071	I-05	HORTOLÂNDIA	152523	IPT/CEDEC	2013	0	44	38	0
219	3519105	I-11	IACANGA	8282	EST	2015	11	20	23	5
220	3519204	I-11	IACRI	6783	NO RISK	2015	0	0	0	0
221	3519253	I-04	IARAS	3054	NO RISK	2015	0	0	0	0
222	3519303	I-12	IBATÉ	26462	NO RISK	2015	0	0	0	0
223	3519402	I-08	IBIRÁ	9447	NO RISK	2015	0	0	0	0
224	3519501	I-11	IBIRAREMA	5701	NO RISK	2015	0	0	0	0
225	3519600	I-07	IBITINGA	46620	EST	2015	55	104	132	29
226	3519709	I-04	IBIÚNA	64384	CBH-RB	2013	72	0	45	30
227	3519808	I-12	ICÉM	6772	EST	2015	11	19	19	4
228	3519907	I-10	IEPÊ	7257	NO RISK	2015	0	0	0	0
229	3520004	I-07	IGARAÇU DO TIETÊ	22614	NO RISK	2015	0	0	0	0
230	3520103	I-08	IGARAPAVA	25925	EST	2015	37	66	74	16
231	3520202	I-03	IGARATÁ	8292	IPT/CEDEC	2014	0	188	0	0
232	3520301	I-01	IGUAPE	27427	CBH-RB	2011	510	0	3	30
233	3520400	I-03	ILHABELA	20836	IG/CEDEC	2008	40	140	233	38
234	3520426	I-01	ILHA COMPRIDA	6704	CBH-RB	2011	0	0	1	30
235	3520442	I-14	ILHA SOLTEIRA	23996	EST	2015	13	29	73	15
236	3520509	I-05	INDAIATUBA	147050	IPT/CEDEC	2014	0	63	0	0
237	3520608	I-09	INDIANA	4932	EST	2015	10	17	14	3
238	3520707	I-08	INDIAPORÃ	4058	NO RISK	2015	0	0	0	0
239	3520806	I-10	INÚBIA PAULISTA	3318	EST	2015	6	10	11	2
240	3520905	I-11	IPAUSSU	12553	IG/CEDEC	2008	102	3	1	0
241	3521002	I-04	IPERÓ	18384	CPRM/CEDEC	2015	0	0	5	0
242	3521101	I-05	IPEÚNA	4340	NO RISK	2015	0	0	0	0
243	3521150	I-08	IPIGUÁ	3476	NO RISK	2015	0	0	0	0
244	3521200	I-15	IPORANGA	4562	CBH-RB	2011	0	0	2	13
245	3521309	I-10	IPUÃ	11870	EST	2015	22	38	34	19
246	3521408	I-05	IRACEMÁPOLIS	15555	IPT/CEDEC	2015	0	0	0	0
247	3521507	I-08	IRAPUÃ	6658	NO RISK	2015	0	0	0	0
248	3521606	I-14	IRAPURU	7457	EST	2015	15	25	23	16
249	3521705	I-15	ITABERÁ	18911	NO RISK	2015	0	0	0	0
250	3521804	I-10	ITAÍ	21039	EST	2015	54	85	70	13
251	3521903	I-08	ITAJOBI	14230	NO RISK	2015	0	0	0	0
252	3522000	I-07	ITAJU	2638	NO RISK	2015	0	0	0	0
253	3522109	I-02	ITANHAÉM	71995	IG/CEDEC	2007	363	743	497	38
254	3522158	I-15	ITAOCA	3226	IG/CEDEC	2015	56	52	0	0
255	3522208	M-4	ITAPECERICA DA SERRA	129685	EMPRESA	2013	102	566	234	31
256	3522307	I-04	ITAPETININGA	125559	IPT/CEDEC	2004	0	192	53	211
257	3522406	I-15	ITAPEVA	82866	IPT/CEDEC	2015	0	21	0	0
258	3522505	I-15	ITAPEVI	162433	EST	2015	677	737	906	207
259	3522604	I-05	ITAPIRA	63377	IPT/CEDEC	2013	0	0	0	0
260	3522653	I-15	ITAPIRAPUÃ PAULISTA	3577	CBH-RB	2011	0	0	147	27
261	3522703	M-4	ITÁPOLIS	37750	EST	2015	58	103	115	23
262	3522802	I-15	ITAPORANGA	14354	NO RISK	2015	0	0	0	0
263	3522901	I-12	ITAPUÍ	10371	EST	2015	17	30	29	6
264	3523008	I-07	ITAPURA	3838	EST	2015	9	14	11	2
265	3523107	M-3	ITAQUAQUECETUBA	272942	BOCAINA	2008	21	257	438	184
266	3523206	I-09	ITARARÉ	46554	EST	2015	116	188	132	28
267	3523305	I-01	ITARIRI	13613	CBH-RB	2011	317	4	0	0
268	3523404	I-05	ITATIBA	81197	IPT/CEDEC	2013	0	628	0	0
269	3523503	I-15	ITATINGA	15446	EST	2015	31	53	44	9
270	3523602	I-04	ITIRAPINA	12836	EST	2015	18	32	39	8
271	3523701	I-14	ITIRAPUÃ	5412	NO RISK	2015	0	0	0	0
272	3523800	I-05	ITOBI	7466	NO RISK	2015	0	0	0	0
273	3523909	I-04	ITU	135366	CPRM/CEDEC	2013	0	0	70	160
274	3524006	I-05	ITUPEVA	26166	IPT/CEDEC	2013	47	207	886	0
275	3524105	I-14	ITUVERAVA	36268	NO RISK	2015	0	0	0	0
276	3524204	I-13	JABORANDI	6424	NO RISK	2015	0	0	0	0
277	3524303	I-05	JABOTICABAL	67408	EST	2015	66	129	191	41
278	3524402	I-03	JACAREÍ	191291	BRITO	2014	941	848	561	431
279	3524501	I-08	JACI	4117	NO RISK	2015	0	0	0	0
280	3524600	I-01	JACUPIRANGA	17041	CBH-RB	2011	310	265	0	0
281	3524709	I-05	JAGUARIÚNA	29597	IPT/CEDEC	2013	0	89	0	0
282	3524808	I-06	JALES	46186	EST	2015	57	103	152	47
283	3524907	I-03	JAMBEIRO	3992	BRITO	2014	4	16	0	0
284	3525003	I-08	JANDIRA	91807	EST	2015	125	223	317	125
285	3525102	I-06	JARDINÓPOLIS	30729	NO RISK	2015	0	0	0	0
286	3525201	I-05	JARINU	17041	IPT/CEDEC	2013	0	18	37	0
287	3525300	M-4	JAÚ	112104	EST	2015	195	269	576	69
288	3525409	I-14	JERIQUARA	3280	NO RISK	2015	0	0	0	0

Map Num	IBGE GEOCO	REDEC	City name	Pop	Source	Year	R1	R2	R3	R4
289	3525508	I-07	JOANÓPOLIS	10409	EST	2015	26	41	36	44
290	3525607	I-11	JOÃO RAMALHO	3842	NO RISK	2015	0	0	0	0
291	3525706	I-08	JOSÉ BONIFÁCIO	28714	NO RISK	2015	0	0	0	0
292	3525805	I-11	JÚLIO MESQUITA	4166	NO RISK	2015	0	0	0	0
293	3525854	I-04	JUMIRIM	2196	NO RISK	2015	0	0	0	0
294	3525904	I-05	JUNDIAÍ	323397	IPT	2006	1147	1629	301	135
295	3526001	I-05	JUNQUEIRÓPOLIS	17005	EST	2015	43	69	52	10
296	3526100	I-10	JUQUIÁ	20516	EST	2015	96	110	102	46
297	3526209	M-4	JUQUITIBA	26459	CBH-RB	2011	20	0	0	37
298	3526308	I-03	LAGOINHA	4957	IPT/CEDEC	2014	0	34	0	0
299	3526407	I-04	LARANJAL PAULISTA	22145	IPT/CEDEC	2015	0	12	0	4
300	3526506	I-09	LAVÍNIA	5131	NO RISK	2015	0	0	0	0
301	3526605	I-01	LAVRINHAS	6008	EST	2015	13	22	20	4
302	3526704	I-05	LEME	80757	IPT/CEDEC	2015	0	0	0	0
303	3526803	I-03	LENÇÓIS PAULISTA	55042	EST	2015	72	126	165	34
304	3526902	I-05	LIMEIRA	249046	COBRAPE	2012	47	63	10	121
305	3527009	I-05	LINDÓIA	5331	CPRM	2013	0	0	592	0
306	3527108	I-07	LINS	65952	IPT/CEDEC	2014	0	6	22	0
307	3527207	I-03	LORENA	77990	IPT/CEDEC	2015	0	263	0	0
308	3527256	I-09	LOURDES	2007	NO RISK	2015	0	0	0	0
309	3527306	I-05	LOUVEIRA	23903	IPT/CEDEC	2013	55	13	84	0
310	3527405	I-07	LUCÉLIA	18316	EST	2015	30	51	63	11
311	3527504	I-07	LUCIANÓPOLIS	2154	NO RISK	2015	0	0	0	0
312	3527603	I-06	LUÍS ANTÔNIO	7160	NO RISK	2015	0	0	0	0
313	3527702	I-09	LUIZIÂNIA	4274	NO RISK	2015	0	0	0	0
314	3527801	I-11	LUPÉRCIO	4230	NO RISK	2015	0	0	0	0
315	3527900	I-11	LUTÉCIA	2897	NO RISK	2015	0	0	0	0
316	3528007	I-07	MACATUBA	15752	NO RISK	2015	0	0	0	0
317	3528106	I-08	MACAUBAL	7385	NO RISK	2015	0	0	0	0
318	3528205	I-08	MACEDÔNIA	3761	NO RISK	2015	0	0	0	0
319	3528304	I-08	MAGDA	3421	NO RISK	2015	0	0	0	0
320	3528403	I-04	MAIRINQUE	39975	IG/CEDEC	2005	122	78	99	13
321	3528502	M-3	MAIRIPORÃ	60111	CPRM	2012	0	0	212	2753
322	3528601	I-10	MANDURI	8271	EST	2015	15	26	23	5
323	3528700	I-10	MARABÁ PAULISTA	3699	NO RISK	2015	0	0	0	0
324	3528809	I-04	MARACAÍ	13004	EST	2015	18	31	39	8
325	3528858	I-08	MARAPOAMA	2238	NO RISK	2015	0	0	0	0
326	3528908	I-10	MARIÁPOLIS	3854	NO RISK	2015	0	0	0	0
327	3529005	I-11	MARÍLIA	197342	EST	2015	275	433	955	181
328	3529104	I-08	MARINÓPOLIS	2195	NO RISK	2015	0	0	0	0
329	3529203	I-11	MARTINÓPOLIS	22346	EST	2015	46	77	68	48
330	3529302	I-12	MATÃO	71753	IG/CEDEC	2008	0	70	59	0
331	3529401	M-2	MAUÁ	363392	IPT/CEDEC	2005	140	3784	307	0
332	3529500	I-08	MENDONÇA	3759	NO RISK	2015	0	0	0	0
333	3529609	I-08	MERIDIANO	4025	NO RISK	2015	0	0	0	0
334	3529658	I-08	MESÓPOLIS	1930	NO RISK	2015	0	0	0	0
335	3529708	I-14	MIGUELÓPOLIS	19019	NO RISK	2015	0	0	0	0
336	3529807	I-07	MINEIROS DO TIETÊ	11410	NO RISK	2015	0	0	0	0
337	3529906	I-01	MIRACATU	22383	CBH-RB	2011	389	86	0	20
338	3530003	I-08	MIRA ESTRELA	2596	NO RISK	2015	0	0	0	0
339	3530102	I-10	MIRANDÓPOLIS	25936	EST	2015	32	59	73	16
340	3530201	I-09	MIRANTE DO PARANAPANEMA	16213	EST	2015	59	88	49	10
341	3530300	I-10	MIRASSOL	48327	EST	2015	51	97	158	30
342	3530409	I-08	MIRASSOLÂNDIA	3741	NO RISK	2015	0	0	0	0
343	3530508	I-08	MOCOCA	65574	EST	2015	150	206	296	40
344	3530607	M-3	MOGI DAS CRUZES	124228	IPT/CEDEC	2013	20	21	255	0
345	3530706	I-05	MOGI-GUAÇU	81467	IPT/CEDEC	2015	0	148	9	0
346	3530805	I-05	MOGI MIRIM	330241	IPT/CEDEC	2014	0	11	3	0
347	3530904	I-05	MOMBUCA	3107	CPRM/CEDEC	2015	0	0	6	0
348	3531001	I-08	MONÇÕES	2055	NO RISK	2015	0	0	0	0
349	3531100	I-02	MONGAGUÁ	35098	IG/CEDEC	2007	22	308	301	106
350	3531209	I-05	MONTE ALEGRE DO SUL	6321	IPT/CEDEC	2015	0	18	0	0
351	3531308	I-06	MONTE ALTO	43613	IG/CEDEC	2008	0	8	5	20
352	3531407	I-05	MONTE APRAZÍVEL	18413	EST	2015	22	42	52	11
353	3531506	I-08	MONTE AZUL PAULISTA	19553	EST	2015	36	62	60	12
354	3531605	I-13	MONTE CASTELO	4089	EST	2015	11	17	12	3
355	3531704	I-10	MONTEIRO LOBATO	3615	EST	2015	13	18	15	173
356	3531803	I-05	MONTE MOR	37340	CPRM	2013	0	0	405	0
357	3531902	I-14	MORRO AGUDO	25428	NO RISK	2015	0	0	0	0
358	3532009	I-03	MORUNGABA	9911	EST	2015	14	25	28	6
359	3532058	I-12	MOTUCA	3871	NO RISK	2015	0	0	0	0
360	3532108	I-09	MURUTINGA DO SUL	3971	NO RISK	2015	0	0	0	0
361	3532157	I-10	NANTES	2269	NO RISK	2015	0	0	0	0
362	3532207	I-10	NARANDIBA	3743	NO RISK	2015	0	0	0	0
363	3532306	I-03	NATIVIDADE DA SERRA	6952	BRITO	2014	21	8	15	0

Map Num	IBGE GEOCO	REDEC	City name	Pop	Source	Year	R1	R2	R3	R4
364	3532405	I-05	NAZARÉ PAULISTA	14410	IPT/CEDEC	2014	0	45	28	8
365	3532504	I-08	NEVES PAULISTA	8907	NO RISK	2015	0	0	0	0
366	3532603	I-08	NHANDEARA	10194	NO RISK	2015	0	0	0	0
367	3532702	I-08	NIPOÃ	3267	NO RISK	2015	0	0	0	0
368	3532801	I-05	NOVA ALIANÇA	4768	EST	2015	5	10	13	3
369	3532827	I-08	NOVA CAMPINA	7295	EST	2015	57	68	23	4
370	3532843	I-08	NOVA CANAÃ PAULISTA	2483	NO RISK	2015	0	0	0	0
371	3532868	I-09	NOVA CASTILHO	991	NO RISK	2015	0	0	0	0
372	3532900	I-15	NOVA EUROPA	7307	EST	2015	7	14	21	4
373	3533007	I-12	NOVA GRANADA	17020	EST	2015	25	45	48	10
374	3533106	I-10	NOVA GUATAPORANGA	2087	NO RISK	2015	0	0	0	0
375	3533205	I-08	NOVA INDEPENDÊNCIA	2063	EST	2015	7	11	6	47
376	3533254	I-08	NOVAIS	3225	NO RISK	2015	0	0	0	0
377	3533304	I-09	NOVA LUZITÂNIA	2749	NO RISK	2015	0	0	0	0
378	3533403	I-05	NOVA ODESSA	42071	IPT/CEDEC	2013	9	21	0	0
379	3533502	I-09	NOVO HORIZONTE	32432	EST	2015	40	74	92	20
380	3533601	I-14	NUPORANGA	6309	NO RISK	2015	0	0	0	0
381	3533700	I-11	OCAUÇU	4164	NO RISK	2015	0	0	0	0
382	3533809	I-11	ÓLEO	2994	NO RISK	2015	0	0	0	0
383	3533908	I-08	OLÍMPIA	46013	EST	2015	52	95	167	28
384	3534005	I-08	ONDA VERDE	3413	NO RISK	2015	0	0	0	0
385	3534104	I-11	ORIENTE	5884	NO RISK	2015	0	0	0	0
386	3534203	I-08	ORINDIÚVA	4161	NO RISK	2015	0	0	0	0
387	3534302	I-13	ORLÂNDIA	36004	EST	2015	31	62	102	22
388	3534401	M-4	OSASCO	652593	IPT/CEDEC	2006	13121	9824	3253	2433
389	3534500	I-11	OSCAR BRESSANE	2552	NO RISK	2015	0	0	0	0
390	3534609	I-14	OSVALDO CRUZ	29648	EST	2015	38	68	93	18
391	3534708	I-11	OURINHOS	93868	IPT/CEDEC	2015	0	0	3	0
392	3534757	I-08	OUROESTE	6290	NO RISK	2015	0	0	0	0
393	3534807	I-10	OURO VERDE	7148	EST	2015	28	42	20	4
394	3534906	I-10	PACAEMBU	12518	EST	2015	21	37	35	8
395	3535002	I-08	PALESTINA	9100	NO RISK	2015	0	0	0	0
396	3535101	I-10	PALMARES PAULISTA	8437	EST	2015	13	24	26	5
397	3535200	I-08	PALMEIRA D´OESTE	10322	NO RISK	2015	0	0	0	0
398	3535309	I-11	PALMITAL	20701	NO RISK	2015	0	0	0	0
399	3535408	I-08	PANORAMA	13649	EST	2015	30	49	39	8
400	3535507	I-10	PARAGUAÇU PAULISTA	39618	EST	2015	70	114	129	24
401	3535606	I-03	PARAÍBUNA	17009	BRITO	2014	86	202	453	75
402	3535705	I-08	PARAÍSO	5429	NO RISK	2015	0	0	0	0
403	3535804	I-11	PARANAPANEMA	15510	EST	2015	41	66	47	9
404	3535903	I-08	PARANAPUÃ	3632	NO RISK	2015	0	0	0	0
405	3536000	I-15	PARAPUÃ	11104	EST	2015	22	38	31	7
406	3536109	I-11	PARDINHO	4732	EST	2015	7	13	13	3
407	3536208	I-01	PARIQUERA-AÇU	17649	CBH-RB	2011	126	0	0	2
408	3536257	I-08	PARISI	1948	NO RISK	2015	0	0	0	0
409	3536307	I-04	PATROCÍNIO PAULISTA	11416	EST	2015	15	27	38	7
410	3536406	I-10	PAULICÉIA	5302	NO RISK	2015	0	0	0	0
411	3536505	I-05	PAULÍNIA	51326	IPT/CEDEC	2013	0	20	0	0
412	3536570	I-07	PAULISTÂNIA	1779	NO RISK	2015	0	0	0	0
413	3536604	I-08	PAULO DE FARIA	8472	NO RISK	2015	0	0	0	0
414	3536703	I-14	PEDERNEIRAS	36614	EST	2015	56	98	119	22
415	3536802	I-05	PEDRA BELA	5609	CPRM/CEDEC	2015	0	0	148	0
416	3536901	I-08	PEDRANÓPOLIS	2734	NO RISK	2015	0	0	0	0
417	3537008	I-14	PEDREGULHO	14994	NO RISK	2015	0	0	0	0
418	3537107	I-05	PEDREIRA	35219	CPRM	2012	0	0	22	0
419	3537156	I-11	PEDRINHAS PAULISTA	2861	NO RISK	2015	0	0	0	0
420	3537206	I-01	PEDRO DE TOLEDO	9187	CBH-RB	2011	93	27	0	22
421	3537305	I-09	PENÁPOLIS	54635	NO RISK	2015	0	0	0	0
422	3537404	I-09	PEREIRA BARRETO	25028	NO RISK	2015	0	0	0	0
423	3537503	I-04	PEREIRAS	6226	NO RISK	2015	0	0	0	0
424	3537602	I-02	PERUÍBE	51451	IG/CEDEC	2008	90	1460	446	130
425	3537701	I-07	PIACATU	4625	EST	2015	13	20	13	3
426	3537800	I-04	PIEDADE	50131	IG/CEDEC	2006	5	43	141	1
427	3537909	I-09	PILAR DO SUL	23948	EST	2015	49	81	78	49
428	3538006	I-03	PINDAMONHANGABA	126026	BRITO	2014	402	34	1	0
429	3538105	I-04	PINDORAMA	13109	EST	2015	16	30	37	8
430	3538204	I-08	PINHALZINHO	10986	EST	2015	19	33	33	44
431	3538303	I-05	PIQUEROBI	3478	EST	2015	8	13	11	2
432	3538501	I-10	PIQUETE	15200	EST	2015	21	35	70	2355
433	3538600	I-05	PIRACAIA	23347	IPT/CEDEC	2014	0	92	0	0
434	3538709	I-05	PIRACICABA	329158	IPT/CEDEC	2014	0	346	2	300
435	3538808	I-03	PIRAJU	27897	EST	2015	51	88	79	17
436	3538907	I-15	PIRAJUÍ	20095	EST	2015	35	61	57	12
437	3539004	I-13	PIRANGI	10038	NO RISK	2015	0	0	0	0
438	3539103	M-4	PIRAPORA DO BOM JESUS	12395	NO RISK	2015	0	0	0	0

Map Num	IBGE GEOCO	REDEC	City name	Pop	Source	Year	R1	R2	R3	R4
439	3539202	I-07	PIRAPOZINHO	22104	EST	2015	38	65	67	14
440	3539301	I-10	PIRASSUNGA	64864	EST	2015	58	112	224	40
441	3539400	I-05	PIRATININGA	10584	EST	2015	11	21	30	6
442	3539509	I-06	PITANGUEIRAS	31156	NO RISK	2015	0	0	0	0
443	3539608	I-08	PLANALTO	3670	NO RISK	2015	0	0	0	0
444	3539707	I-11	PLATINA	2867	NO RISK	2015	0	0	0	0
445	3539806	M-3	POÁ	95801	IG/CEDEC	2008	17	264	340	916
446	3539905	I-08	POLONI	4774	NO RISK	2015	0	0	0	0
447	3540002	I-07	POMPÉIA	18171	EST	2015	23	43	51	23
448	3540101	I-11	PONGAÍ	3693	EST	2015	7	12	12	2
449	3540200	I-06	PONTAL	29681	NO RISK	2015	0	0	0	0
450	3540259	I-07	PONTALINDA	3539	EST	2015	13	20	10	2
451	3540309	I-08	PONTES GESTAL	2539	NO RISK	2015	0	0	0	0
452	3540408	I-08	POPULINA	4450	NO RISK	2015	0	0	0	0
453	3540507	I-04	PORANGABA	6652	CPRM/CEDEC	2015	0	0	20	0
454	3540606	I-04	PORTO FELIZ	45514	IPT/CEDEC	2015	0	75	60	0
455	3540705	I-12	PORTO FERREIRA	47437	IPT/CEDEC	2015	70	267	35	0
456	3540754	I-08	POTIM	13605	EST	2015	17	30	46	8
457	3540804	I-08	POTIRENDABA	13656	NO RISK	2015	0	0	0	0
458	3540853	I-03	PRACINHA	1431	EST	2015	5	7	5	1
459	3540903	I-06	PRADÓPOLIS	12912	NO RISK	2015	0	0	0	0
460	3541000	I-10	PRAIA GRANDE	193582	EST	2015	307	512	798	243
461	3541059	I-02	PRATÂNIA	3950	EST	2015	10	17	11	2
462	3541109	I-07	PRESIDENTE ALVES	4317	NO RISK	2015	0	0	0	0
463	3541208	I-04	PRESIDENTE BERNARDES	14662	EST	2015	16	31	48	9
464	3541307	I-10	PRESIDENTE EPITÁCIO	39298	EST	2015	90	145	137	24
465	3541406	I-10	PRESIDENTE PRUDENTE	189186	EST	2015	217	351	921	116
466	3541505	I-10	PRESIDENTE VENCESLAU	37347	EST	2015	41	74	144	23
467	3541604	I-10	PROMISSÃO	31105	EST	2015	34	64	95	19
468	3541653	I-04	QUADRA	2651	IPT/CEDEC	2015	0	6	0	0
469	3541703	I-07	QUATÁ	11655	EST	2015	17	30	33	7
470	3541802	I-11	QUEIROZ	2171	NO RISK	2015	0	0	0	0
471	3541901	I-11	QUELUZ	9112	EST	2015	24	38	28	47
472	3542008	I-11	QUINTANA	5443	NO RISK	2015	0	0	0	0
473	3542107	I-05	RAFARD	8360	IPT/CEDEC	2015	0	0	67	0
474	3542206	I-03	RANCHARIA	28772	EST	2015	37	68	88	32
475	3542305	I-03	REDENÇÃO DA SERRA	4047	BRITO	2014	67	14	0	0
476	3542404	I-10	REGENTE FEIJÓ	16998	EST	2015	26	46	48	10
477	3542503	I-10	REGINÓPOLIS	4742	EST	2015	12	19	14	3
478	3542602	I-01	REGISTRO	53752	CBH-RB	2011	205	500	0	60
479	3542701	I-07	RESTINGA	5584	EST	2015	14	22	18	3
480	3542800	I-15	RIBEIRA	3507	CBH-RB	2011	0	0	41	0
481	3542909	I-14	RIBEIRÃO BONITO	11246	EST	2015	15	27	37	18
482	3543006	I-15	RIBEIRÃO BRANCO	21231	NO RISK	2015	0	0	0	0
483	3543105	I-14	RIBEIRÃO CORRENTE	3881	NO RISK	2015	0	0	0	0
484	3543204	I-11	RIBEIRÃO DO SUL	4497	NO RISK	2015	0	0	0	0
485	3543238	I-12	RIBEIRÃO DOS ÍNDIOS	2222	EST	2015	4	7	6	1
486	3543253	I-15	RIBEIRAO GRANDE	7390	IPT/CEDEC	2004	60	2	0	0
487	3543303	I-10	RIBEIRÃO PIRES	104508	EST	2015	129	214	487	350
488	3543402	I-06	RIBEIRÃO PRETO	504923	IPT/CEDEC	2006	0	6	535	180
489	3543501	M-2	RIVERSUL	7192	EST	2015	42	57	21	4
490	3543600	I-14	RIFAINA	3325	NO RISK	2015	0	0	0	0
491	3543709	I-12	RINCÃO	10330	IG/CEDEC	2008	0	15	0	0
492	3543808	I-11	RINÓPOLIS	10255	EST	2015	30	47	29	6
493	3543907	I-05	RIO CLARO	168218	IPT/CEDEC	2014	0	130	6	0
494	3544004	I-05	RIO DAS PEDRAS	23494	CPRM/CEDEC	2015	0	0	11	0
495	3544103	M-2	RIO GRANDE DA SERRA	37091	IG/CEDEC	2005	273	481	326	0
496	3544202	I-08	RIOLÂNDIA	8560	EST	2015	21	34	24	5
497	3544251	I-15	ROSANA	24229	EST	2015	32	56	87	28
498	3544301	I-03	ROSEIRA	8577	BRITO	2014	114	0	0	0
499	3544400	I-09	RUBIÁCEA	2337	NO RISK	2015	0	0	0	0
500	3544509	I-10	RUBINÉIA	2615	EST	2015	5	9	7	2
501	3544608	I-08	SABINO	4951	EST	2015	8	15	14	3
502	3544707	I-10	SAGRES	2439	NO RISK	2015	0	0	0	0
503	3544806	I-08	SALES	4563	NO RISK	2015	0	0	0	0
504	3544905	I-14	SALES OLIVEIRA	9325	NO RISK	2015	0	0	0	0
505	3545001	M-3	SALESÓPOLIS	14357	IG/CEDEC	2005	2	3	0	2
506	3545100	I-10	SALMOURÃO	4401	NO RISK	2015	0	0	0	0
507	3545159	I-05	SALTINHO	5799	NO RISK	2015	0	0	0	0
508	3545209	I-04	SALTO	93159	IPT/CEDEC	2015	0	25	8	0
509	3545308	I-04	SALTO DE PIRAPORA	35072	IPT/CEDEC	2015	0	0	0	0
510	3545407	I-11	SALTO GRANDE	8444	NO RISK	2015	0	0	0	0
511	3545506	I-10	SANDOVALINA	3089	NO RISK	2015	0	0	0	0
512	3545605	I-07	SANTA ADÉLIA	13449	EST	2015	19	35	38	8
513	3545704	I-08	SANTA ALBERTINA	5586	NO RISK	2015	0	0	0	0
514	3545803	I-05	SANTA BÁRBARA D	170078	IPT/CEDEC	2013	0	42	0	0

Map Num	IBGE GEOCO	REDEC	City name	Pop	Source	Year	R1	R2	R3	R4
			OESTE							
515	3546009	I-08	SANTA BRANCA	13010	EST	2015	22	36	55	19
516	3546108	I-08	SANTA CLARA D`OESTE	2123	NO RISK	2015	0	0	0	0
517	3546207	I-05	SANTA CRUZ DA CONCEIÇÃO	3531	NO RISK	2015	0	0	0	0
518	3546256	I-06	SANTA CRUZ DA ESPERANÇA	1796	NO RISK	2015	0	0	0	0
519	3546306	I-05	SANTA CRUZ DAS PALMEIRAS	25556	NO RISK	2015	0	0	0	0
520	3546405	I-11	SANTA CRUZ DO RIO PARDO	40919	IPT/CEDEC	2015	0	32	9	0
521	3546504	I-03	SANTA ERNESTINA	5741	EST	2015	8	15	16	4
522	3546603	I-08	SANTA FÉ DO SUL	26512	NO RISK	2015	0	0	0	0
523	3546702	I-05	SANTA GERTRUDES	15906	CPRM/CEDEC	2015	0	0	32	0
524	3546801	M-3	SANTA ISABEL	43740	IPT/CEDEC	2013	0	595	410	0
525	3546900	I-12	SANTA LÚCIA	7853	NO RISK	2015	0	0	0	0
526	3547007	I-05	SANTA MARIA DA SERRA	4673	NO RISK	2015	0	0	0	0
527	3547106	I-10	SANTA MERCEDES	2803	NO RISK	2015	0	0	0	0
528	3547205	I-08	SANTANA DA PONTE PENSA	1894	NO RISK	2015	0	0	0	0
529	3547304	M-4	SANTANA DE PARNAÍBA	74828	CPRM	2013	0	0	1371	0
530	3547403	I-08	SANTA RITA D´OESTE	2695	NO RISK	2015	0	0	0	0
531	3547502	I-12	SANTA RITA DO PASSA QUATRO	26138	EST	2015	25	49	74	16
532	3547601	I-12	SANTA ROSA DO VITERBO	21435	EST	2015	22	42	65	13
533	3547650	I-08	SANTA SALETE	1379	NO RISK	2015	0	0	0	0
534	3547700	I-06	SANTO ANASTÁCIO	20749	EST	2015	31	55	63	13
535	3547809	M-2	SANTO ANDRÉ	649331	CPRM	2013	0	0	8894	0
536	3547908	I-06	SANTO ANTÔNIO DA ALEGRIA	5764	NO RISK	2015	0	0	0	0
537	3548005	I-05	SANTO ANTONIO DE POSSE	18124	IPT/CEDEC	2014	30	50	20	0
538	3548054	I-10	SANTO ANTÔNIO DO ARACANGUÁ	6929	EST	2015	17	27	21	4
539	3548104	I-05	SANTO ANTONIO DO JARDIM	6154	NO RISK	2015	0	0	0	0
540	3548203	I-03	SANTO ANTÔNIO DO PINHAL	6328	IPT/CEDEC	2014	0	47	123	0
541	3548302	I-10	SANTO EXPEDITO	2526	NO RISK	2015	0	0	0	0
542	3548401	I-09	SANTÓPOLIS DO AGUAPEÍ	3816	NO RISK	2015	0	0	0	0
543	3548500	I-02	SANTOS	417983	IPT	2012	0	1815	2598	694
544	3548609	I-09	SÃO BENTO DO SAPUCAÍ	10355	EST	2015	21	35	34	44
545	3548708	I-03	SÃO BERNARDO DO CAMPO	703177	EST	2015	806	1253	3457	1273
546	3548807	M-2	SÃO CAETANO DO SUL	140159	IPT/CEDEC	2014	0	204	158	0
547	3548906	I-12	SÃO CARLOS	192998	IPT/CEDEC	2015	0	55	0	0
548	3549003	I-08	SÃO FRANCISCO	2863	NO RISK	2015	0	0	0	0
549	3549102	M-2	SÃO JOÃO DA BOA VISTA	77387	EST	2015	77	141	307	47
550	3549201	I-08	SÃO JOÃO DAS DUAS PONTES	2660	NO RISK	2015	0	0	0	0
551	3549250	I-09	SÃO JOÃO DE IRACEMA	1671	NO RISK	2015	0	0	0	0
552	3549300	I-05	SÃO JOÃO DO PAU D´ALHO	2180	EST	2015	6	10	7	1
553	3549409	I-14	SÃO JOAQUIM DA BARRA	41587	NO RISK	2015	0	0	0	0
554	3549508	I-14	SÃO JOSÉ DA BELA VISTA	8075	NO RISK	2015	0	0	0	0
555	3549607	I-03	SÃO JOSÉ DO BARREIRO	4143	IPT/CEDEC	2015	0	22	3	0
556	3549706	I-10	SÃO JOSÉ DO RIO PARDO	50077	EST	2015	54	101	164	31
557	3549805	I-08	SÃO JOSÉ DO RIO PRETO	358523	IG/CEDEC	2012	102	3	4	1
558	3549904	I-03	SÃO JOSÉ DOS CAMPOS	539313	BRITO	2014	67	630	135	160
559	3549953	M-4	SÃO LOURENÇO DA SERRA	12199	CBH-RB	2011	0	34	3	10
560	3550001	I-03	SÃO LUÍZ DO PARAITINGA	10429	BRITO	2014	88	99	287	175
561	3550100	I-05	SÃO MANUEL	36545	EST	2015	51	92	112	22
562	3550209	I-04	SÃO MIGUEL ARCANJO	30798	EST	2015	70	116	87	19
563	3550308	M-1	SÃO PAULO	10434252	IPT-SP	2011	14005	62470	20979	8057
564	3550407	I-05	SÃO PEDRO	27897	CPRM	2013	0	0	25	40
565	3550506	I-04	SÃO PEDRO DO TURVO	6888	EST	2015	15	25	21	16
566	3550605	I-04	SÃO ROQUE	66637	IPT/CEDEC	2004	3	12	57	3
567	3550704	I-03	SÃO SEBASTIÃO	58038	IG/CEDEC	2006	207	1005	1504	423
568	3550803	I-11	SÃO SEBASTIÃO DA GRAMA	12454	EST	2015	23	40	36	8
569	3550902	I-06	SÃO SIMÃO	13675	NO RISK	2015	0	0	0	0
570	3551009	I-02	SÃO VICENTE	303551	IPT/CEDEC	2012	60	133	122	20

Map Num	IBGE GEOCO	REDEC	City name	Pop	Source	Year	R1	R2	R3	R4
571	3551108	I-05	SARAPUÍ	7805	EST	2015	21	33	24	5
572	3551207	I-15	SARUTAIÁ	3739	NO RISK	2015	0	0	0	0
573	3551306	I-08	SEBASTIANÓPOLIS DO SUL	2546	NO RISK	2015	0	0	0	0
574	3551405	I-04	SERRA AZUL	7446	EST	2015	18	29	24	5
575	3551504	I-06	SERRANA	32603	EST	2015	37	70	92	20
576	3551603	I-05	SERRA NEGRA	23851	IPT/CEDEC	2014	0	0	376	0
577	3551702	I-06	SERTÃOZINHO	94664	IG/CEDEC	2008	2	50	100	0
578	3551801	I-01	SETE BARRAS	13714	CBH-RB	2011	80	5	70	21
579	3551900	I-13	SEVERÍNIA	13605	NO RISK	2015	0	0	0	0
580	3552007	I-03	SILVEIRAS	5378	IPT/CEDEC	2015	0	18	4	0
581	3552106	I-05	SOCORRO	32704	IPT/CEDEC	2014	0	0	799	14
582	3552205	I-04	SOROCABA	493468	IG/CEDEC	2005	74	335	388	376
583	3552304	I-09	SUD MENUCCI	7365	NO RISK	2015	0	0	0	0
584	3552403	I-05	SUMARÉ	196723	CPRM	2013	0	0	2188	0
585	3552502	M-3	SUZANO	2790	FUNEP	2006	497	229	162	53
586	3552551	I-06	SUZANÓPOLIS	2790	EST	2015	7	11	9	2
587	3552601	I-08	TABAPUÃ	10493	NO RISK	2015	0	0	0	0
588	3552700	I-12	TABATINGA	12990	NO RISK	2015	0	0	0	0
589	3552809	M-4	TABOÃO DA SERRA	197644	FIPT	2007	5284	2164	1490	229
590	3552908	I-10	TACIBA	5221	NO RISK	2015	0	0	0	0
591	3553005	I-09	TAGUAÍ	7468	EST	2015	15	25	21	5
592	3553104	I-13	TAIAÇU	5619	NO RISK	2015	0	0	0	0
593	3553203	I-13	TAIÚVA	5506	NO RISK	2015	0	0	0	0
594	3553302	I-15	TAMBAÚ	22258	EST	2015	30	56	63	14
595	3553401	I-05	TANABI	22587	EST	2015	32	58	74	27
596	3553500	I-04	TAPIRAÍ	8570	CBH-RB	2011	12	13	0	38
597	3553609	I-05	TAPIRATIBA	12942	IPT/CEDEC	2015	0	18	0	1
598	3553658	I-06	TAQUARAL	2722	NO RISK	2015	0	0	0	0
599	3553708	I-12	TAQUARITINGA	52065	IPT/CEDEC	2016	0	13	0	0
600	3553807	I-15	TAQUARITUBA	21982	NO RISK	2015	0	0	0	0
601	3553856	I-15	TAQUARIVAÍ	4473	NO RISK	2015	0	0	0	0
602	3553906	I-10	TARABAÍ	5786	NO RISK	2015	0	0	0	0
603	3553955	I-11	TARUMÃ	10743	NO RISK	2015	0	0	0	0
604	3554003	I-04	TATUÍ	93430	IPT/CEDEC	2015	3	152	15	0
605	3554102	I-03	TAUBATÉ	244165	BRITO	2014	385	47	66	36
606	3554201	I-08	TEJUPÁ	5336	EST	2015	26	36	16	3
607	3554300	I-15	TEODORO SAMPAIO	20003	EST	2015	40	67	61	12
608	3554409	I-13	TERRA ROXA	7752	NO RISK	2015	0	0	0	0
609	3554508	I-04	TIETÊ	31710	IPT/CEDEC	2015	15	5	0	2
610	3554607	I-11	TIMBURI	2731	NO RISK	2015	0	0	0	0
611	3554656	I-04	TORRE DE PEDRA	2144	IPT/CEDEC	2015	0	42	0	0
612	3554706	I-05	TORRINHA	8837	NO RISK	2015	0	0	0	0
613	3554755	I-12	TRABIJU	1380	NO RISK	2015	0	0	0	0
614	3554805	I-03	TREMEBÉ	34823	BRITO	2014	261	249	3	16
615	3554904	I-08	TRÊS FRONTEIRAS	5159	NO RISK	2015	0	0	0	0
616	3554953	I-05	TUIUTI	4956	IPT/CEDEC	2015	0	7	0	0
617	3555000	I-10	TUPÃ	63333	EST	2015	85	150	230	39
618	3555109	I-11	TUPI PAULISTA	13286	EST	2015	22	38	38	8
619	3555208	I-09	TURIÚBA	1895	NO RISK	2015	0	0	0	0
620	3555307	I-08	TURMALINA	2366	NO RISK	2015	0	0	0	0
621	3555356	I-08	UBARANA	4220	NO RISK	2015	0	0	0	0
622	3555406	I-03	UBATUBA	66861	IG/CEDEC	2006	691	1572	2470	368
623	3555505	I-07	UBIRAJARA	4156	NO RISK	2015	0	0	0	0
624	3555604	I-08	UCHOA	9035	NO RISK	2015	0	0	0	0
625	3555703	I-08	UNIÃO PAULISTA	1354	NO RISK	2015	0	0	0	0
626	3555802	I-08	URÂNIA	8825	NO RISK	2015	0	0	0	0
627	3555901	I-07	URU	1404	NO RISK	2015	0	0	0	0
628	3556008	I-10	URUPÊS	11833	EST	2015	16	28	37	7
629	3556107	I-08	VALETIM GENTIL	8605	IPT/CEDEC	2015	0	13	0	0
630	3556206	I-05	VALINHOS	82973	IPT/CEDEC	2013	0	23	127	0
631	3556305	I-08	VALPARAÍSO	18574	EST	2015	24	44	53	11
632	3556354	I-05	VARGEM	6975	NO RISK	2015	0	0	0	0
633	3556404	I-09	VARGEM GRANDE DO SUL	36302	EST	2015	43	80	103	22
634	3556453	M-4	VARGEM GRANDE PAULISTA	32683	IPT/CEDEC	2013	0	177	4	0
635	3556503	I-05	VÁRZEA PAULISTA	92800	IPT/CEDEC	2006	2140	646	2410	300
636	3556602	I-05	VERA CRUZ	11085	EST	2015	21	37	31	7
637	3556701	I-05	VINHEDO	47215	IPT/CEDEC	2013	0	29	206	29
638	3556800	I-13	VIRADOURO	15962	NO RISK	2015	0	0	0	0
639	3556909	I-13	VISTA ALEGRE DO ALTO	4754	NO RISK	2015	0	0	0	0
640	3556958	I-08	VITÓRIA BRASIL	1675	NO RISK	2015	0	0	0	0
641	3557006	I-04	VOTORANTIM	95925	IG/CEDEC	2005	92	275	211	88
642	3557105	I-08	VOTUPORANGA	75641	IPT/CEDEC	2015	0	37	0	0
643	3557154	I-08	ZACARIAS	1947	NO RISK	2015	0	0	0	0

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644	3557204	I-11	CHAVANTES	12194	EST	2015	28	46	38	7
645	3557303	I-05	ESTIVA GERBI	8856	CPRM/CEDEC	2015	0	0	70	0