Geostatistical strategy to build Spatial Coastal-Flooding Models

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Geostatistical strategy to build Spatial Coastal-Flooding Models

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Abstract

The intensification of flooding events in urban coastal areas and the management of the extremely vulnerable ecosystems has become a global issue and has been the subject of several studies in recent decades. The combination of statistical modelling techniques and geospatial analysis has gained prominence in integrated management of natural hazards. Combined approach represents a promising strategy to reduce complexity, providing a holistic representation of the system. However, for applying planning and risk management alternatives in urban space of coastal areas, the causal relationships between environmental and anthropogenic factors distribution and the flooding sites have to be well clarified. This article aimed to propose a new strategy to build Spatial Coastal-Flooding Models based on records of flooding points occurred and environmental and anthropogenic characteristics of the area. The strategy was designed to combine simple but robust statistical techniques and relate geospatially data obtained from free and easily accessible online databases. The geostatistical strategy was applied in a coastal city of Brazil, where high environmental vulnerability and constantly flooding are observed. The strategy finds that the relationships between environmental and anthropogenic variables and flooding events are not homogeneous over space. The results indicate that the strategy can be easily replicable and refined through the inclusion of other factors of influence, obtaining good precision in the representation and explanation of the flooding events in coastal areas. In general, the strategy provides information that can support decision-making by government agencies in relation to integrated urban planning and mitigation of flooding risk coastal areas.

Key words: Biophysical vulnerability; Coastal environments; Flooding management; Geospatial analysis; Parameter regression technique.

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Conflicts of interest

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Authors' contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Jakcemara Caprario, Paula Lidia Santana, Larissa Thainá Schmitt Azevedo and Fernando Kit Wu. The first draft of the manuscript was written by Jakcemara Caprario and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

1 INTRODUCTION

Floods are the most significant and most expensive natural disaster to which modern society is exposed. Simonovic (2009) estimates that about 520 million people are affected annually, causing about 25,000 deaths and at least US$60 billion in economic losses. The combined action between high population density, anthropogenic changes in the environment and climate change further aggravate the problem of flooding worldwide (Wahab and Tiong 2016). Recent climate change related events, such as higher intensity precipitation events, extreme temperatures, and rising sea level, have been exposing the vulnerability of urban environment, including the increased flooding risks on a regional scale, especially in coastal areas (Akbarpour and Niksokhan 2018; Durand et al. 2018; Pasquier et al. 2018). The incidence of flooding in the world's urban coastal areas is estimated to be 100 times higher by the end of the century (IPCC 2014).

The impacts of natural hazards on the coastal environment go far beyond the political-administrative territorial units. Coastal areas are densely populated and have city centres located at low terrain elevation, being susceptible to different disaster, such as coastal, river or urban flooding, rising tides, and saltwater intrusion into groundwater (Azevedo de Almeida and Mostafavi 2016; Durand et al. 2018; Malik and Abdalla 2016; Pasquier et al. 2018). Local governments are responsible for managing these aspects within their jurisdiction. However, the task of analysing and proposing prevention and control measures of flooding in coastal areas is complex. Thus, developing management policies for coastal areas requires an understanding of the multiple factors involved and their interactions in the socioeconomic-environmental context (Perrone et al. 2020).

In coastal cities in developing countries these problems become even more critical. The vulnerability to extreme weather events is high and the capacity to manage flooding is low (Ogie et al. 2019). The scarcity of fiscal and technological resources and the lack of adequate urban planning prevail in these countries. This has repercussions on the management and control of disaster risks, which are essentially reactive (Fadel et al. 2018; Kovacs et al. 2017; Wang et al. 2016). With financial restrictions, funds for public projects are generally used for basic needs, i.e., drinking water and food supply, affecting flooding management and leading to significant economic and social consequences. There are also concerns about the mismanagement of public funds that should have been spent on flooding mitigation measures and to minimise the scarcity of recorded data to support decision-making (Ogie et al. 2019). In Brazil, the fifth largest country in the world in terms of territory and population, considered an emerging power with the sixteenth largest coastal extension, the situation is no different.

With about 9000 km of coastline and 17 states bordering the Atlantic Ocean, Brazil has a variety of climatic and environmental conditions expressing its potential for coastal studies (Gomes da Silva et al. 2016). The country constantly suffers from extreme events of precipitation, storms and rising sea levels and, as a result, flooding is a recurring annual problem that affects millions of people (Pezzoli and Cartacho 2013). The lack of historical records and monitored data makes it difficult to verify flooding levels in most of the Brazilian coastal cities. Therefore, flooding management suffers from uncertain planning and inadequate preparation (Gomes da Silva et al. 2016; Ogie et al. 2019). Considering the inefficiency in allocating government resources, as well as the lack of monitoring data and the need for low complexity computational methodologies, new strategies that simplify the process and at the same time provide a holistic representation of the system are required.

The combination of statistical modelling techniques and geospatial analysis provides an effective tool for reducing the complexity of large-scale data sets and identifies relationships between their components (Menció et al. 2012; Zhu et al. 2017). Due to their simplicity in terms of data requirements, low cost of operation and quick execution, these methods have worldwide applicability (Nandi et al. 2016; Ogie et al. 2019), covering the most diverse areas. Some studies have analysed superficial and underground recharge flows or aquifer vulnerability (e.g., Boy-Roura et al. 2013; Güler et al. 2012; Long and Valder 2011; Morris et al. 2008; Zhu et al. 2017). Others have evaluated the hydro energetic performance (e.g., Asbahi et al. 2019; Jaramillo et al. 2018), or space-time characterized stream temperatures and droughts (e.g.,Gocic and Trajkovic 2014; Guillemette et al. 2009). Others still have built snow gliding, air quality or ecosystem services models from spatial correlation (e.g., Jumaah et al. 2019; Leitinger et al. 2008; Lyu et al. 2019). Few studies have even considered the application of these techniques in the area of pluvial and river flooding management (e.g., Nandi et al. 2016; Wang et al. 2016); however, the application of these techniques in coastal flooding planning and control has not been evidenced.

Physical processes in coastal environments are not necessarily easy to quantify and model, since many interactions are involved (Perrone et al. 2020). The coastal projects should consider the lessons learned from past events (Pezzoli and Cartacho 2013). The study of historical events and their relationship with possible environmental and anthropogenic factors can facilitate the understanding of the

flooding occurrence and provide significant information to urban planning (Wang et al. 2016). The spatial distribution of flooding events is dependent upon local geological, geographical, topographical, climatological, hydrological and anthropogenic factors (Nandi et al. 2016). Hence, the selection of variables that best express the behaviour of these environments is a key factor for coastal flooding management.

Therefore, this article proposes a new strategy denominated MEIC (Modelo Espacial de Inundação Costeira - Spatial Coastal-Flooding Models) to develop flooding models based on the association between the spatial distribution of flooding points and their links with the environmental and anthropogenic characteristics of the area. The strategy was designed to combine statistical techniques and geospatial analysis between data obtained from free and easily accessible online databases. Instead using information from the causes of flooding (pluvial and tidal databases that are absent or insufficient) the methodology seeks to gather the information from the consequences of flooding. In addition, the models seek to fill the information gap on the hydrological, topographical and geological interactions that occur in the area and to relate the impact of anthropogenic activities on the flooding occurrence. The strategy was applied in a coastal city located in the southern region of Brazil, where high environmental vulnerabilities and constant urban and coastal flooding are observed, representing the reality of most coastal developing countries. The results provide information that can support decision-making by government agencies in both developed and developing countries, seeking socially and economically viable alternatives, considering limited resources, in relation to the choice of protection measures and adaptation of existing infrastructure.

2 METHODOLOGY

The bases for application of the MEIC strategy consist in five major steps: (1) data collection of the influencing factors, to create the database for statistical analysis; (2) Principle Component Analysis (PCA), aiming to reduce the number of factors of influence; (3) Cluster Analysis (CA), to group the flooding sites in sub-regions with similar characteristics; (4) Spatial Coastal-Flooding Model, to model, examine, and explore spatial relationships between dependent variables and possible explanatory variables; and (5) Model performance evaluation, aiming to evaluate the statistical quality of the model accuracy and complexity. The conceptual framework of the MEIC strategy is shown in Fig 1.

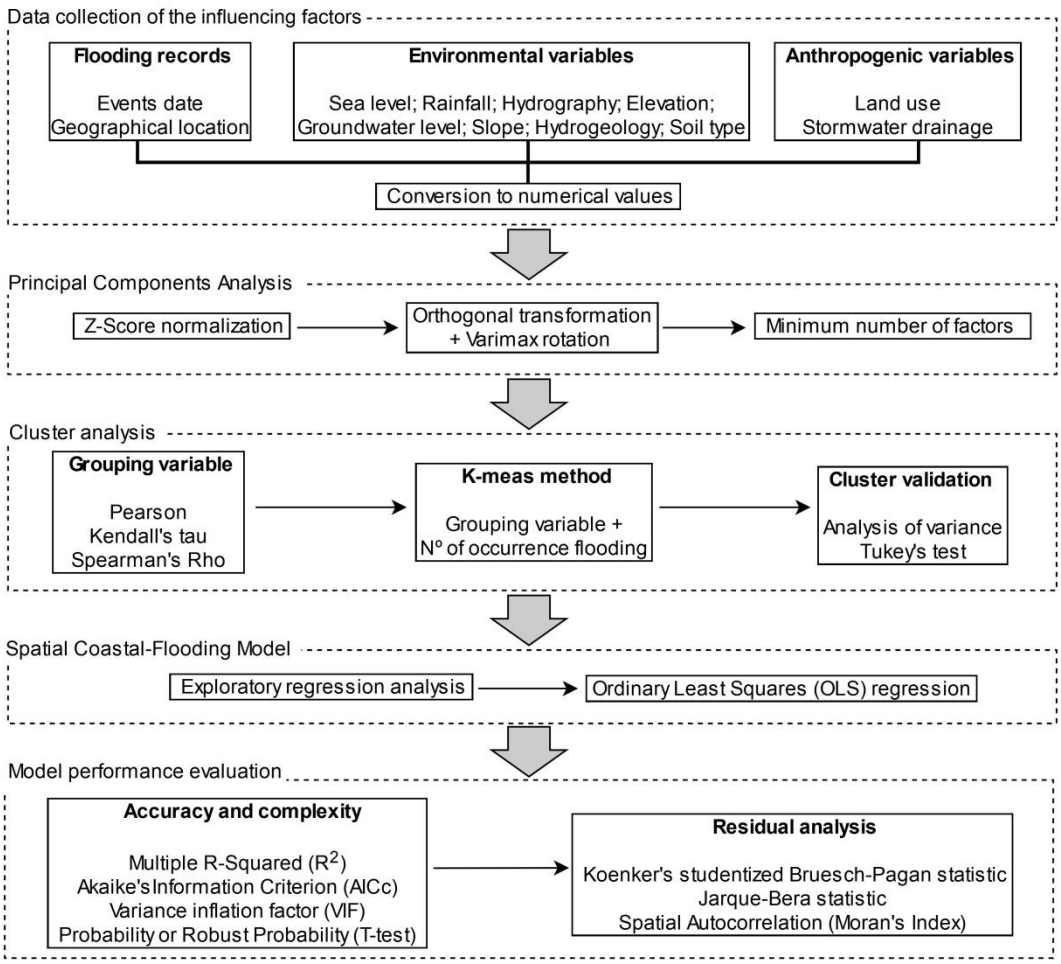

Fig 1 Conceptual framework of methodology

Designed following the basic principles and requirements below:

• Low cost and easy application.

• Data obtained from free and easy accessible online databases.

• Not require advanced skills in programming and Geographic Information System (GIS), but minimum knowledge of statistical treatment.

• Robustness, ensuring statistically significant relationships based on past events.

• Suitable for urbanized coastal areas, requiring flood influencing factors such as sea level data, micro-drainage network, hydrogeology and groundwater level maps.

2.1 DATA COLLECTION OF THE INFLUENCING FACTORS

The focus of the strategy is to explain the flooding occurrence associated mainly with coastal areas. In this way, information regarding flooding events in a previously established area was gathered through documentary analysis in electronic newspapers, televised news, and news websites. The information that was collected is related to the event date and geographical location. The origin of the flooding events was not distinguished, considering pluvial, rivers and coastal flooding.

The unconventional information collection method adopted in this strategy, aims to make up for the lack of monitored data taking advantage of the information mediated by the social system, commonly overlooked in this type of study. In the conventional strategies defined by hydrology, we start from the monitored environmental and hydrological database, going through multi-criteria analysis and modelling, reaching possible flooding areas. In the MEIC strategy, we perform an inverse modelling (Fig 2), starting from the real problem, with information filtered by the social system through the publication of catastrophic events, going through statistical and geospatial modelling techniques, and arriving at the real source of the problem.

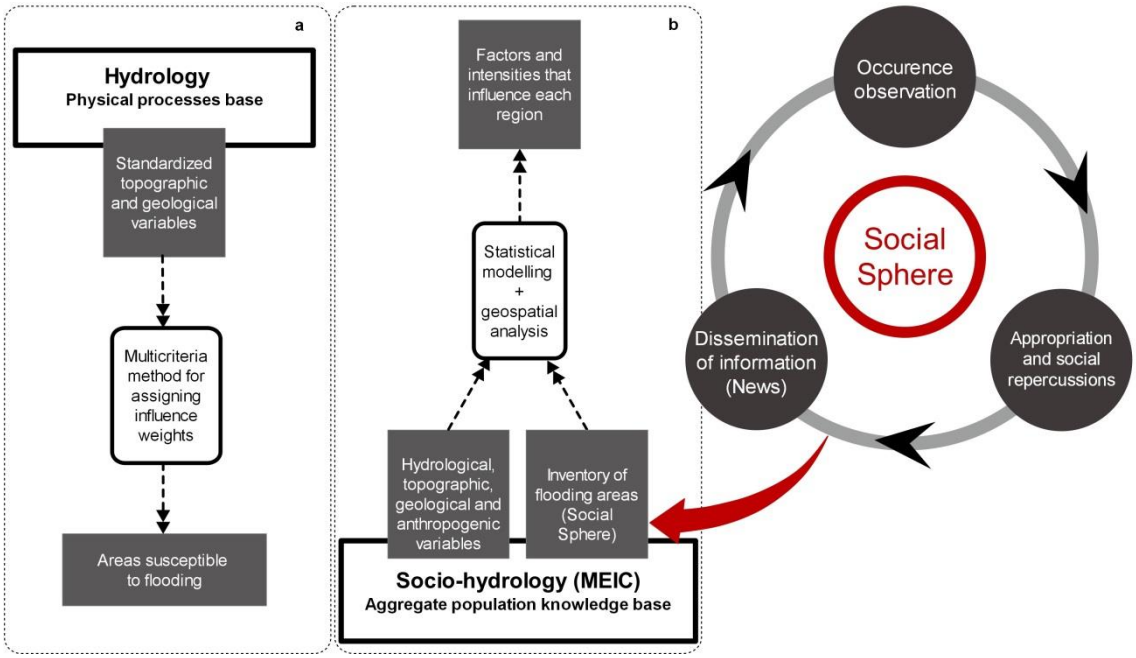

Fig 2 Flowchart diagrams of the spatial modelling. a) Hydrology modelling frame. b) Socio-hydrology modelling frame. In inverse modeling, the population knowledge is aggregated, and the main information is based on the social sphere looping (occurrence observation)

Thus, data were collected regarding the factors of influence of the environmental and anthropogenic variables that operate in each flooding location inventoried. For this purpose, we adopted 10 factors of influence: rainfall, hydrography, elevation, slope, soil type, land use, and stormwater drainage, selected from an urban flooding study conducted by Caprario and Finotti (2019), and sea level, groundwater level, hydrogeology maps where also added to the present study.

All the information gathered was compiled in a spreadsheet, as presented in appendix A. The influencing factors described by site characteristics (e.g. land use, soil type and hydrogeology) were converted into numerical values. The values ranged from 0 to 3 according to the degree of influence on the flooding occurrence and the contribution to runoff (e.g. Table 1). The hydrography and stormwater drainage factors were represented by a binary system, with 0 attributed to the absence and 1 the presence of the factor at the event local.

Table 1 Example of converting local characteristics to numerical values

Factor	Characteristics	Numerical values
Land use	Forest	0
	Undergrowth	1
	Urbanization	2
	Water bodies	3
Hydrogeology	Aquiclude	0
	Sedimentary	1
	Crystalline	2
Hydrography	Absence	0
	Presence	1

Land use - The numerical values of this factor have been converted respecting the condition that the lower human interference the less the chance of flooding. So, areas covered by forest or even undergrowth were considered to have great infiltration capacity, reducing the chances of flooding. The density of vegetation cover is also a differentiating factor between the values. Runoff is more likely in bare fields than in those with good vegetation cover. Urbanized areas, on the other hand, received high value, given the greater possibility of flooding occurrence due to the high rates of impervious surface. It is important to note that for areas covered by water bodies the maximum value was adopted, since they are naturally flooded.

Soil type - Soil texture has a great impact on flooding occurrence. Sandy soils tend to have greater infiltration rates and better internal drainage, characteristics that are the opposite to those of clay soils. For this study, the soil type factor was classified into four categories based on the water absorption conditions, depth and texture. The Acrisols class was considered more susceptible to flooding occurrence than the Arenosols, since its composition normally has a greater amount of clay, making it difficult to infiltrate. The Cambisols class received the lowest value due to its sandy character and location mainly associated with massif areas. It is important to note that mangrove discriminated soil the received the maximum value, since they are naturally flooded.

Hydrogeology - The numerical values of this factor have been converted respecting the condition of hydraulics and soil permeability. So, areas with sedimentary hydrogeology were considered more susceptible to flooding occurrence than the crystalline hydrogeology, receiving less value, given its coarse texture and high permeability that favours the aquifer recharge. Areas classified as aquiclude received the lowest value, due to being directly associated with the highest elevation areas of the land (massif).

2.2 PRINCIPAL COMPONENTS ANALYSIS**.**

The nonparametric multivariate PCA approach was applied to quantify the main relationships among the environmental and anthropogenic variables, and to obtain principal components (PCs) that are most representative of the events. PCA analysis aimed to reducing the number of possible correlated factors into a smaller number of vectors (Luo et al. 2019). PCA was used as a precursor to cluster analysis, as it separate factors that were likely to display collinearity and lead to a more stable clustering result (Morris et al. 2008; Nandi et al. 2016).

Initially, the numerical values of each factor were standardized using z-score normalization to reduce the impacts of magnitude and variability. Subsequently the PCs were derived using Eq. [1]:

$$PC = [E^T].X \qquad [1]$$

where E is the matrix of Eigen vectors $[e_1, e_2, e_3, \dots e_m]$ and $X = [X_1, X_2, X_3, \dots X_m]$ is variable vector. PCs are selected successively to account for the maximum variability in the data (Wahab and Tiong 2016). The number of components to keep is based on the Kaiser criterion, for which only the components with eigenvalues greater than 1 are retained (Zhu et al. 2017).

2.3 CLUSTER ANALYSIS

Several types of hydrological, topographical, geological and anthropogenic variables can have different influences on coastal environments and local urban infrastructures, and thus the frequency and severity of flooding can vary significantly between distinct areas. The interactions among multiple type of variable should not be neglected or underestimated (Wang et al. 2015). With the objective of determine the grouping variable, Pearson (r) parametric correlation methods and Kendall's tau (τ) and Spearman's Rho (ρ) rank non-parametric correlations were applied. These statistical methods are the commonly used in the hydrology to measure the dependence between variables (Tosunoğlu and Onof 2017).

A Spatially Constrained Multivariate Clustering approach was used to sequentially cluster flooding sites. The different sub-regions were clustered based on similarity of the grouping variable and the number of flooding occurrence in each location. The flooding sites were partitioned by the clustering algorithms based on the K-means method. These algorithms minimizes the sum of squared errors within each cluster and therefore is implicitly based on pairwise Euclidean distance (Haaf and Barthel 2018). Convergence of algorithm occurred when partitioning was reduced to the maximum extent or when the centroid of the cluster is relocated, indicating that the solution was locally ideal, according to Sehgal et al. (2018). Cluster centroids were calculated based on the average of all observations in the cluster, where a factor will only be included in a cluster if at least one other cluster member is a nearest-neighbour (Xie et al. 2018).

In order to check if there is a significant difference between the clusters, the Analysis of Variance (ANOVA) technique and Tukey's test were applied with 0.05 significance level. The null hypothesis assumes that the clusters mean variables are equal while the alternative hypothesis states that at least one mean is different. All statistics analysis were performed using the STATISTIC® 8.0 software, and the spatial constraints and models were developed in the ArcGIS® 10.1 software. More detailed information about correlation methods, cluster analysis (CA) and ANOVA can be obtained from (Haaf and Barthel 2018; Sehgal et al. 2018; Tosunoğlu and Onof 2017; Wang et al. 2015; Xie et al. 2018).

2.4 SPATIAL COASTAL-FLOODING MODEL

Ordinary Least Squares (OLS) is the best known of all regression techniques and it has been the starting point for all spatial regression analysis (Jumaah et al. 2019). This analysis allows modelling, examining, and exploring spatial relationships between dependent variables and possible explanatory variables.

The OLS regression model assumes that the spatial relationships between dependent and independent variables are static, that is, it does not vary over space (Wang et al. 2016). This way, the method provides a global model of the factors that one needs to understand by creating the Spatial Coastal-Flooding Model (MEIC), which was represented in each cluster by a single regression equation. OLS regression for k independent factors is specified as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \quad [2]$$

where Y is the dependent variable that can be explained by spatial variables $X_1, X_2, X_3, \ldots X_k$, that is, the input factors causing the flooding; β_0 is the regression intercept that represents the expected value for the dependent variable if all the independent variables are zero; and β_k is the respective regression coefficient for explanatory variable $(X_1, X_2, X_3, \ldots X_k)$. Detailed descriptions of the OLS regression model can be found in Leitinger et al. (2008) and Jumaah et al. (2019).

2.5 MODEL PERFORMANCE EVALUATION

One of the most important steps of MEIC strategy is the performance evaluation of the obtained Spatial Coastal-Flooding Model. The objective of this step was to evaluate the statistical quality of the model accuracy and complexity, in addition to its ability to deal with spatial autocorrelation. The performance of MEIC strategy was evaluated by the values of R^2 (Multiple R-Squared) and AICc (Akaike's Information Criterion). R^2 indicates a model's ability to explain the variance in the dependent variable, and thus a higher R^2 implies a better model performance; a perfect model has $R^2 = 1$. The AICc is an indicator of model accuracy and complexity, hence lower AICc value indicates closer approximation of the model to reality (Mollalo et al. 2020; Tu and Xia 2008).

The variance inflation factor (VIF) and Probability or Robust Probability were also calculated to determine any multi-collinearity among the explanatory factors of the model. For instance, probability values for the used factors in the equation must be less than 0.05, indicating that none of the explanatory variables have an effect on the dependent variable (Mollalo et al. 2020). In addition, T-test was used to assess whether or not an explanatory variable is statistically significant.

The stationarity of the model was evaluated by Koenker (BP) statistic (Koenker's studentized Bruesch-Pagan statistic) and the normality of the computed residues was determined by the Jarque-Bera statistic at the 95% confidence level. Finally, Spatial Autocorrelation (Moran's Index) checked the spatially random of the regression residual. The value of Moran's Index range from −1 to 1, where a value of 0 indicates perfect spatial randomness. If there is significant spatial autocorrelation in a regression model, it violates the assumption of randomly distributed and independent residues (Mollalo et al. 2020; Tu and Xia 2008). Thus, the efficiency of the model would be considered suspect and the results would not be reliable.

3 APLICATION

The proposed strategy was applied in Florianópolis city, located in Santa Catarina State, in the southern region of Brazil. The city has area of 432km² and a population of 500,000 inhabitants in 2019. The city is surrounded by the Atlantic Ocean, with the island portion (97% of the territory) being separated from the mainland by the Florianópolis Bay. The region is influenced by environmental characteristics, mainly by the density of water resources, mangrove vegetation and direct influence of tidal variation. In addition to its high environmental vulnerability, it has poor coverage of the stormwater drainage system (characterized as absolute separator) and is constantly affected by pluvial flooding, river flooding and coastal flooding (Caprario and Finotti 2019).

For the application of the MEIC strategy, the locations of flooding events in Florianópolis from 2013 to 2019 were inventoried from documentary records published in local media. The raw data consisted of 108 photographic records; where each record described a site that was inundated during a specific flooding event, totalizing 60 distinct points distributed between the main regions of urban and commercial occupation (Fig 3). The duration and depth values for each flooding event were not available

in most records. Therefore, only the inundation frequency was used to describe the flooding occurrence in Florianópolis City.

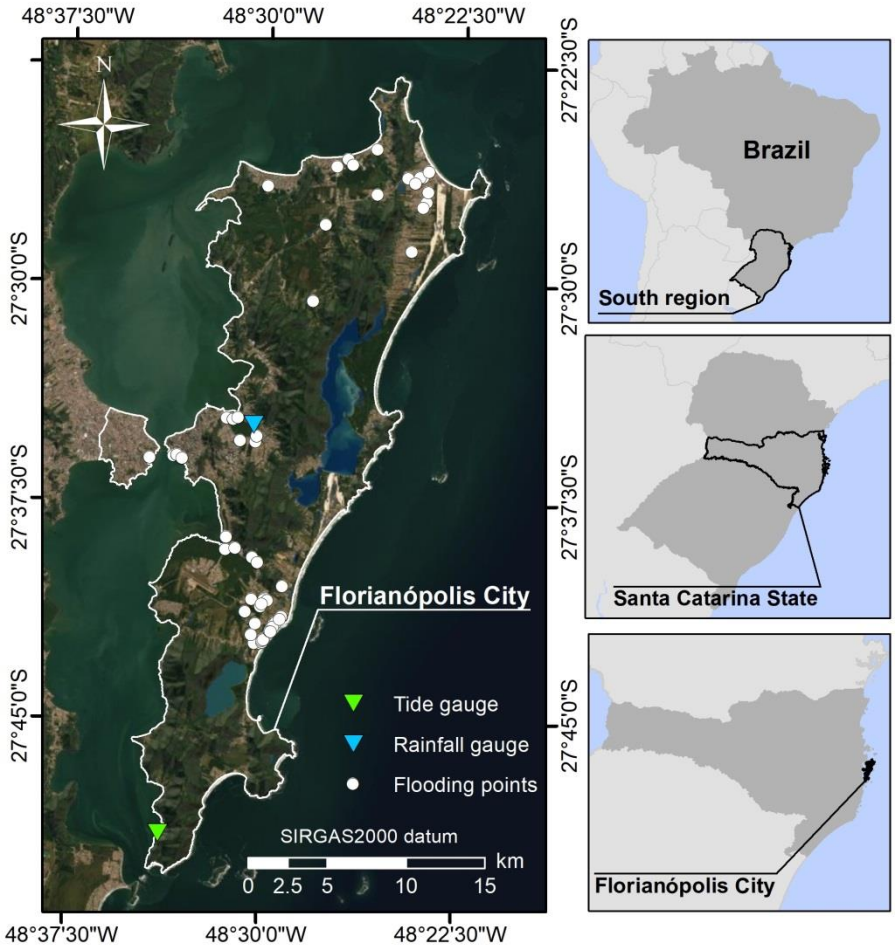

Fig 3 Location of Florianópolis City with locations of flooding occurrence

A spatial database was constructed for the Florianópolis City identifying information about 6 of the 10 flooding influencing factors for all points inventoried. In addition, missing spatial information such as maximum daily sea level, daily accumulated rainfall, land use and the presence of a stormwater drainage system at the site of the inventoried points were investigated in loco or on a nearby gauge, standard procedure for application of the MEIC strategy. The information that composes the database referring to the ten flooding influencing factors was collected from online and free databases, as shown in Table 2. Fig 4 shows the spatial data used in 6 of the 10 flooding influencing factors considered in the strategy.

Table 2 Data used to create spatial database of flooding influencing factors

Variables	Influencing factors	Units	Observations	Source
Hydrological	Groundwater level	m	Generated from 178 static level points to a 2-m grid.	CPMR, 2013
	Daily sea level	cm	Maximum sea level measured on the day the flooding occurred.	EPAGRI, 2019
	Daily rainfall	mm	Accumulated precipitation on the day the flooding occurred.	EPAGRI, 2019
	Hydrography	-	Presence or absence of water bodies at the flooding occurrence site.	IPUF, 2014
Topographical	Elevation (DEM)	m	Generated from contour lines with 5 meter contour interval to a 1-m grid.	IPUF, 2000
	Slope	%	Generated from DEM to a 100-m grid.	IPUF, 2000

Geological	Hydrogeology	-	Scale of 1:500,000	CPRM, 2013
	Soil type	-	Scale of 1:250,000	EMBRAPA, 2004
Anthropogenic	Land use	-	Class with the highest predominance at the flooding occurrence site.	In loco
	Stormwater drainage	-	Presence or absence of stormwater drainage infrastructure at the flooding occurrence site.	In loco

CPRM – Companhia de Pesquisa de Recursos Minerais (Mineral Resources Research Company)
EPAGRI – Empresa de Pesquisa Agropecuária e Extensão Rural de Santa Catarina (Agricultural Research and Rural Extension of Santa Catarina)
IPUF – Instituto de Planejamento Urbano de Florianópolis (Urban Planning Institute of Florianópolis)
EMBRAPA – Empresa Brasileira de Pesquisas Agropecuárias (Brazilian Agricultural Research Corporation)

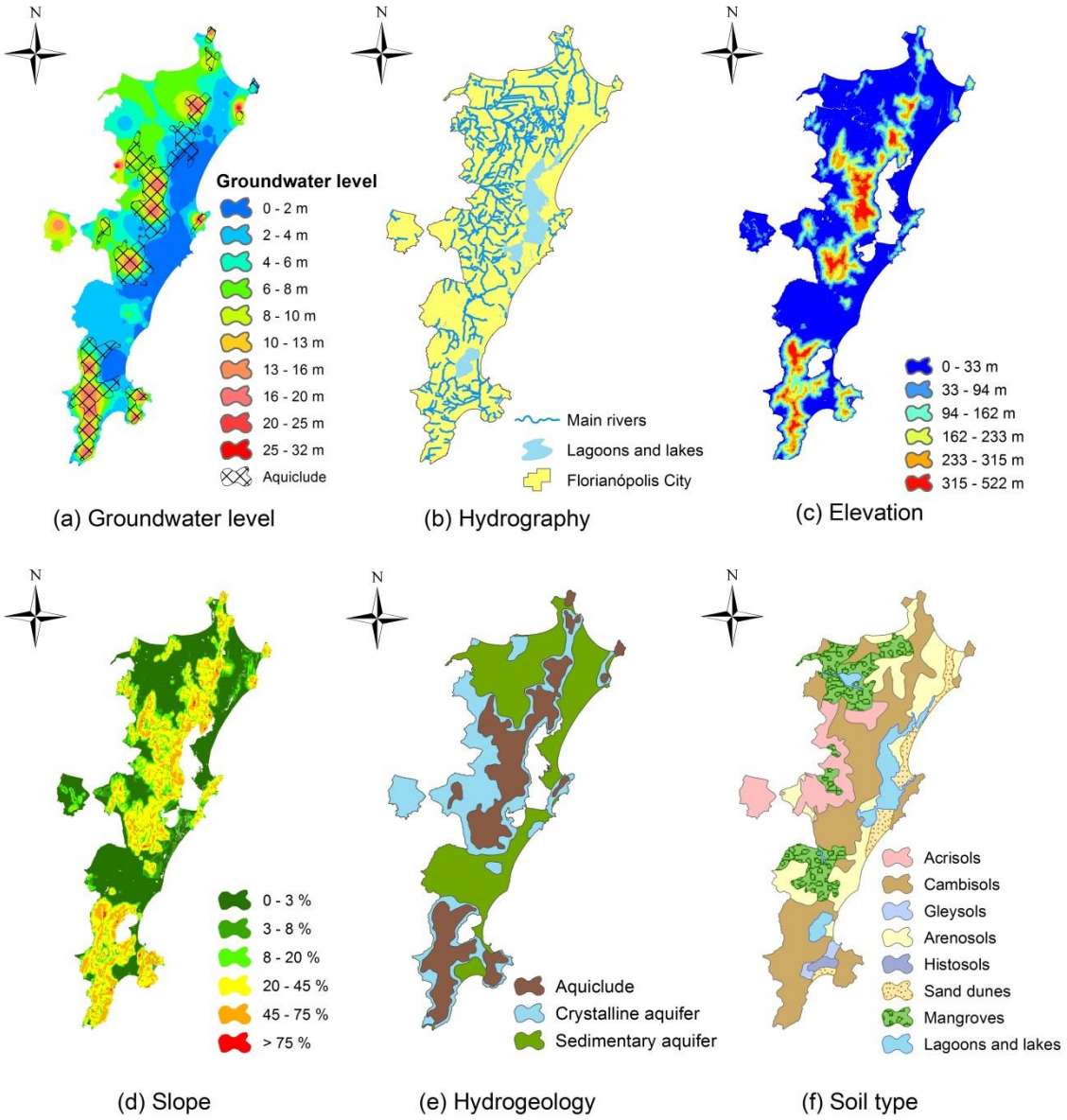

Fig 4 Spatial representation of factors groundwater level (a), hydrography (b), elevation (c) slope (d), hydrogeology (e), and soil type (f)

4 RESULTS AND DISCUSSIONS

4.1 FACTORS AFFECTING THE FLOODING OCCURRENCE

From the standardized environmental and anthropogenic variables in this study, the principal components were extracted on the correlation matrix computed for the 10 flooding influencing factors. As a result, only the first four components extracted were in conformity with the Kaiser criterion, presenting eigenvalues greater than 1. They explained about 70% of the total variance in spatial and temporal distribution of the flooding occurrence. To maximize the variance of the first four principal axes, the Varimax normalized rotation was applied (in accordance with Cloutier et al. 2008; Güler et al. 2012; Zhu et al. 2017). The interactions between the factors for these four principal components are reported in Table 3, as well as their respective explained variance.

Table 3 Principal component loadings and explained variance for the four components with Varimax normalized rotation

Factors	Principal components			
	PC1	PC2	PC3	PC4
Sea level	0.287	**0.860**	0.019	0.144
Rainfall	0.183	**-0.826**	0.277	0.111
Elevation	**-0.618**	0.133	-0.507	0.144
Hydrography	**0.887**	0.141	0.048	0.008
Stormwater drainage	0.215	-0.057	0.219	**0.741**
Land use	**0.667**	-0.411	-0.095	0.057
Soil type	**0.842**	0.150	-0.044	-0.004
Hydrogeology	0.140	-0.219	**0.844**	0.035
Slope	-0.246	0.077	-0.211	**0.665**
Groundwater level	-0.432	0.078	**0.631**	0.015
Eigenvalue	2.752	1.714	1.551	1.051
Cumulative eigenvalue	2.752	4.466	6.017	7.068
Explained variance (%)	27.518	17.140	15.507	10.510
Cumulative % of variance	27.518	44.658	60.165	70.675

Bold and underlined values: loadings >0.6 (significant interactions)

Each variable loaded strongly onto only one of four principal components, showing a clear identifiable relationship with flooding occurrence.

First component (PC1) explains the greatest amount of the variance (27.5%), and is characterized by the higher loadings to hydrography, soil type and land use (loadings >0.6). They also have the highest negative correlation with the elevation factor. So, sites with presence of hydrography, clay soils (Acrisols), densely urbanized and with low terrain elevation tend to have a higher occurrence of flooding events. This component reflects all types of environmental and anthropogenic variables established in study. Because of the association between the land use factors, elevation and hydrography, component 1 is defined as the component "urbanization" in reference to the process of development and urban occupation.

PC2 contains only hydrological variables, explaining 17.1% of the variance. This component was defined as the component "storm surge" because of its highly positive loading with the sea level factor. This positive loading is possibly consistent with the increase in storm surge events, rising tide and sea level rise, reported for the entire south coast of Brazil (Gomes da Silva et al. 2016). However, this component still presented highly negative loading with the rainfall factor. The negative loading for the rainfall, in opposition to the positive of the sea level, can be justified by the low levels of accumulated daily rainfall, less than 2 mm, characterizing approximately 53% of the inventoried events. These low rainfall levels are directly associated with information on the rise in the maximum daily sea level, which in these events ranged between 50 and 100 cm above the reference.

Component PC3 is defined as the "underground" component because of its positive loadings with the hydrogeology factor and groundwater level, the only two underground components adopted in the study. This component contains 15.5% of the variance, suggesting that the studied flooding events are influenced by presence of fractured crystalline aquifers and superficiality of groundwater level in the study area. It also indicates that all of the studied flooding sites are to some extent dependent, or related to the underground water flow of the coastal area.

Finally, component PC4 contains 10.5% of the variance and it is defined as the "stormwater" component because of its positive loadings in stormwater drainage factor and slope, the two factors often related to the urban stormwater drainage system. Therefore, sites with a predominance of large areas of coastal plains (slope of 0-3%) and that do not have a stormwater drainage system tend to have more cases of flooding.

4.2 SPATIAL CLUSTER OF FLOODING SITES

After applying PCA and identifying the minimum number of factors that should be used for constructing the spatial coastal-flooding model, the grouping variable was determined, i.g., the factor that has the highest significant statistical correlation. This grouping variable will be used together with the number of flooding occurrences, thus defining the conditions of spatial constriction and avoiding multi-collinearity between the influencing factors. Parametric and non-parametric correlation coefficients for all factors influencing the flooding occurrence observed in the study area are presented in appendix B. The flooding influencing factors had both positive and negative correlations. The highest significant correlation of 0.760 was obtained between hydrography and soil type, while the lowest significant correlation of -0.168 was detected between hydrography and groundwater level. Trends of the factors of influence were considered statistically significant at the 5% significance level using the Pearson test, Kendall's tau test and the Spearman's Rho test. The results of the parametric and non-parametric tests confirm the strong correlation between the factors hydrography and soil type. As both factors do not vary in time, only in space, the hydrography factor was defined as grouping variable. The choice of this factor between the two correlates was based on the general results of the PCA, where hydrography presented the higher loading among all the factors analysed.

The frequency of flooding at different spatial scales changes, largely depending on geographical locations, environmental characteristics, anthropogenic changes, and local hydrological factors themselves. Three main clusters could be obtained using the K-means cluster based on the number of events and the grouping variable. Fig 5 shows the geographical location of the three clusters (C1, C2 and C3). It corresponds to the area between the massif under the influence of the largest mangrove in the region (Rio Tavares), east and south of Florianópolis under the influence of lakes, lagoons and outcrops the aquifer, and north and west of Florianópolis under the influence of the Ratones, Saco Grande and Itacorubi mangroves, respectively.

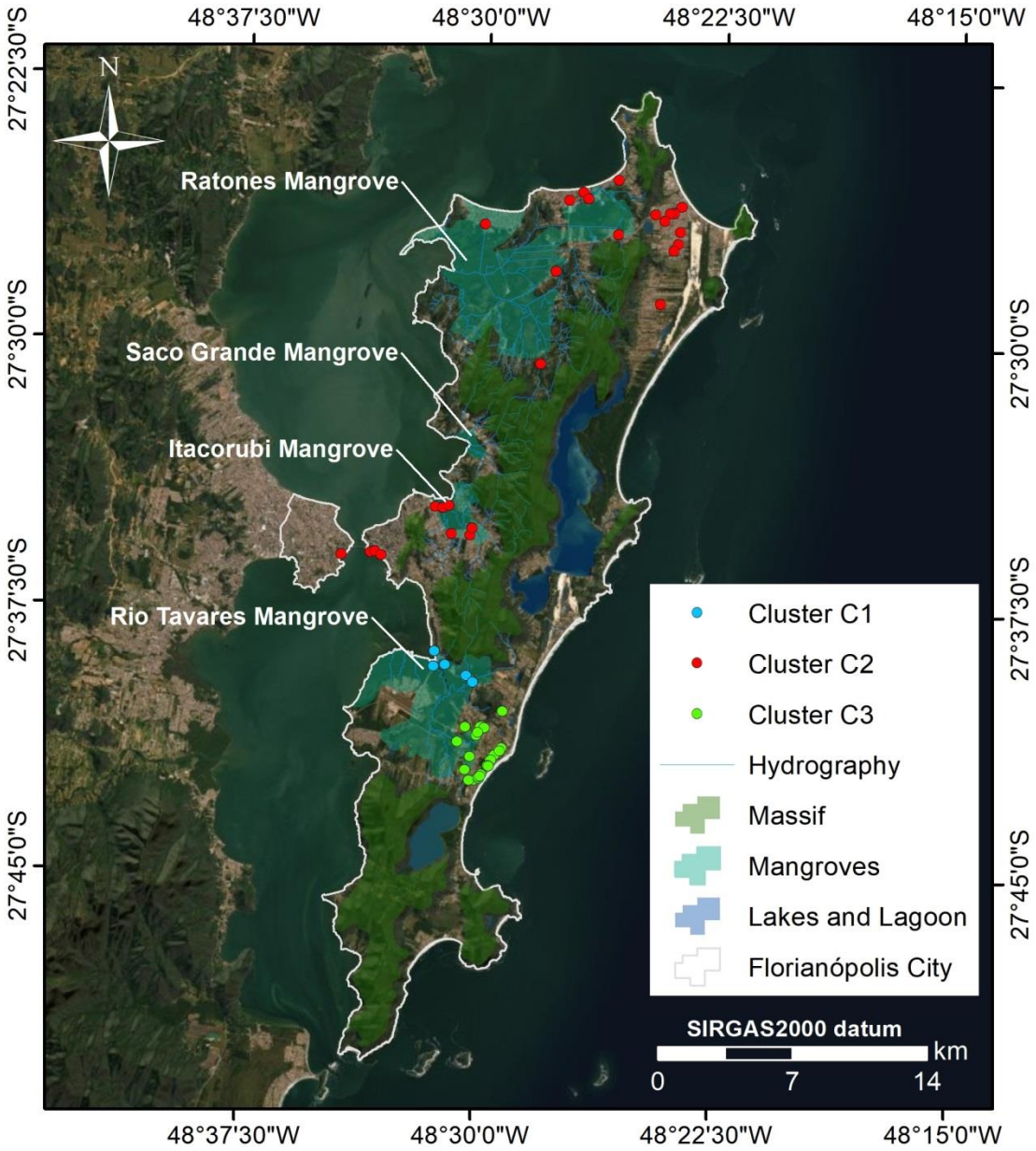

Fig 5 Flooding sites locations and classification according to the spatial constraint multivariate clustering (K-means)

The results of ANOVA and the Tukey test to verify the significant difference between the clusters are shown in Table 4 and Table 5, respectively. The results show that these three clusters are possibly heterogeneous regions ($F_0 > F_{0.05,2,105}=3.09$), e.g., the clusters are statistically different from each other at the 0.05 significance level.

Table 4 ANOVA results for flooding clusters

Source of variation	Sum of squares	Degree of freedom	Mean square	F_0
Clusters	25.921	2	12.960	16.784
Error	81.079	105	0.772	
Total	107.000	107		

Table 5 Tukey test result for flooding clusters

Tukey test			Cluster	Mean
a			C1	0.829
	b		C2	0.079
		c	C3	-0.574

4.3 SPATIAL COASTAL-FLOODING MODEL AND PERFORMANCE EVALUATION

Through an Ordinary Least Squares regression, all possible combinations of the 10 influencing factors were explored to obtain an explanation of the observed flooding occurrence for each sub-region. Summary of the best regression results in C1, C2, and C3 sub-regions are shown in Table 6, Table 7 and Table 8 respectively.

Table 6 Summary of regression results in Sub-region C1

Factor	Coefficient	StdError	T-test	Probability	Robust probability	VIF
Intercept	0.119	0.194	0.614	0.548	0.188	----
Sea level	0.885	0.174	5.097	0.000*	0.000*	4.148
Rainfall	0.447	0.184	2.433	0.028*	0.007*	3.967
Hydrography	1.302	0.261	4.994	0.000*	0.000*	5.342
Hydrogeology	1.577	0.290	5.432	0.000*	0.000*	6.119
F statistic: F(4,15) = 12.088*				Wald Statistic = 938.441*		
R^2 = 0.763				Koenker (BP) Statistic = 5.806		
Adj R^2 = 0.700				Jarque-Bera Statistic = 4.460		
AICc = 41.858				Moran's Index = 0.086		

VIF = Variance Inflation Factor (value >7.5 indicate redundancy among factors); N= 20; R^2 = Multiple R-Squared; Adj R^2 = Adjusted R-Squared; AICc = Akaike Information Criterion; *p<0.05

Table 7 Summary of regression results in Sub-region C2

Factor	Coefficient	StdError	T-test	Probability	Robust probability	VIF
Intercept	-0.087	0.101	-0.858	0.395	0.358	----
Hydrography	-0.308	0.128	-2.408	0.020*	0.128	2.805
Land use	0.346	0.086	4.044	0.000*	0.000*	1.969
Soil type	-0.361	0.134	-2.697	0.009*	0.098	2.501
Hydrogeology	0.605	0.088	6.839	0.000*	0.000*	1.277
F statistic: F(4,47) = 25.020*				Wald Statistic = 98.478*		
R^2 = 0.680				Koenker (BP) Statistic = 4.242		
Adj R^2 = 0.653				Jarque-Bera Statistic = 4.970		
AICc = 98.105				Moran's Index = - 0.041		

VIF = Variance Inflation Factor (value >7.5 indicate redundancy among factors); N= 52; R^2 = Multiple R-Squared; Adj R^2 = Adjusted R-Squared; AICc = Akaike Information Criterion; *p<0.05

Table 8 Summary of regression results in Sub-region C3

Factor	Coefficient	StdError	T-test	Probability	Robust probability	VIF
Intercept	-0.747	0.136	-5.490	0.000*	0.000*	----
Rainfall	-0.256	0.150	-1.713	0.096	0.009*	1.039
Elevation	0.396	0.153	2.579	0.015*	0.012*	1.044
Stormwater drainage	0.255	0.078	3.273	0.003*	0.000*	1.025
F statistic: F(3,32) = 7.178*				Wald Statistic = 17.531*		
R^2 = 0.402				Koenker (BP) Statistic = 28.269*		
Adj R^2 = 0.346				Jarque-Bera Statistic = 0.891		
AICc = 68.637				Moran's Index = - 0.047		

VIF = Variance Inflation Factor (value >7.5 indicate redundancy among factors); N= 36; R^2 = Multiple R-Squared; Adj R^2 = Adjusted R-Squared; AICc = Akaike Information Criterion; *p<0.05

Once the regression analysis has been completed, three analytical models of the spatial distributions of coastal flooding have been constructed. The modelling equations that have been constructed for the C1, C2 and C3 sub-regions are indicated in Equations (3, 4, and 5) respectively.

$$\mathbf{MEIC_{C1}} = \mathbf{0.119} + \mathbf{0.885}\,\boldsymbol{S} + \mathbf{0.447}\,\boldsymbol{R} + \mathbf{1.302}\,\boldsymbol{H} + \mathbf{1.577}\,\boldsymbol{G} \quad [3]$$

$$\mathrm{MEIC_{C2}} = -0.087 - 0.308\,H + 0.346\,L - 0.361\,T + 0.605\,G \quad [4]$$

$$\mathrm{MEIC_{C3}} = -0.747 - 0.256\,R + 0.396\,E + 0.255\,D \quad [5]$$

where, MEIC represents the Spatial Coastal-Flooding Model, S (cm) represents the sea level, R (mm) represents the rainfall, H represents the hydrography, G represents Hydrogeology, L represents the land use, T represents the soil type, E (m) represents the elevation, and D represents the stormwater drainage.

These equations do not produce the absolute values of the occurrence of coastal flooding but denote to the closed or near approximated to the real value. The significance of coefficients represents the best optimization of value that can be estimated (Jumaah et al. 2019).

Among the 10 factors considered, 8 were able to explain the flooding occurrence in the sub-regions, being excluded by the regression models the Groundwater level and Slope factors. The factors maintained by the regression models were provided by different combinations, with only one constant of the hydrological type variables in all sub-regions.

The $MEIC_{C1}$ performed well in the spatial modelling of coastal flooding events for the sub-region C1, explaining 76% of the occurrences ($R^2 = 0.763$) with the best approximation to reality (AICc = 41.858) among all models built. The VIF of these factors were relatively low, ranging from 3.967 to 6.119, which indicate that there was no significant multi-collinearity. Additionally, the explanatory variable were all statistically significant ($p < 0.05$). The model also ensured stationarity (Koenker = 5.806), normality (Jarque-Bera = 4.460) and spatial randomness of residues (Moran's I = 0.086), demonstrating that it is adequate to explain the relationships between the number of floods and the factors of influence (Table 6).

The results suggest that the sub-region C1 is mainly affected by variables of the hydrological and geological type, with the flooding events being explained by the sea level rise, high rainfall levels, presence of local hydrography and porous bedrock (unconsolidated sedimentary aquifer). Despite the high permeability of the rocky basement, it has low soil depth, being considered an aquifer recharge area with several outcrop points. The model of this region indicates the need to prioritize investments aimed at the retention and temporary storage of runoff and coastal engineering works that defend the region from advancing sea level, such as, storm surge barriers or tide gates. This coastal defence measure are often chosen as an alternative to close off estuaries and it has been construct at various locations around the world, for example, The Netherlands, New Orleans, Singapore, St. Petersburg, Venice (Jonkman et al. 2013; Mooyaart and Jonkman 2017).

The $MEIC_{C2}$ performed well in the spatial modelling of coastal flooding events for the sub-region C2, explaining 68% of the occurrences ($R^2 = 0.680$) with good approximation to reality (AICc = 98.105). The VIF of these factors were relatively very low, ranging from 1.277 to 2.805, which indicate that there was no significant multi-collinearity. Additionally, the explanatory variable were all statistically significant ($p < 0.05$). The model also ensured stationarity (Koenker = 4.242), normality (Jarque-Bera = 4.970) and spatial randomness of residues (Moran's I = -0.041), demonstrating that it is adequate to explain the relationships between the number of floods and the factors of influence (Table 7).

The C2 sub-region, in addition to hydrological and geological variables, is also affected by anthropogenic variables. The flooding events in this sub-region are positively impacted by the absence of local hydrography and soils geological constitution with predominance of sandy texture (Arenosol). The factors that support the occurrence of flooding events in this region are related to some areas with a predominance of fractured crystalline bedrock and increasing impervious surfaces by the urbanization. The porosity and permeability of bedrock may influence flooding potential. Highly porous rocks aid the infiltration of rain, reducing flooding potential, whereas the opposite is seen with less porous, compact and impermeable bedrock (Nandi et al. 2016). The model of this region indicates the need to prioritize investments aimed at the storage and infiltration of runoff, such as, compensatory techniques, and also control the local increase of impervious surfaces rates.

Finally, $MEIC_{C3}$ showed poor performance in the spatial modelling of coastal flooding events for the sub-region C3, explaining only 40% of the occurrences ($R^2 = 0.402$) with good approximation to reality (AICc = 68.637). The VIF of these factors were relatively very low, ranging from 1.025 to 1.044, which indicate that there was no significant multi-collinearity. Additionally, the explanatory variable were all statistically significant (pb <0.05). The model ensured normality (Jarque-Bera = 4.970) and spatial randomness of residues (Moran's I = -0.041); however, it failed in stationarity (Koenker = 28.269), not ensured the consistency of relationships in space (Table 8).

In sub-region C3, geological variables are replaced by topographical variables. Flooding events in this sub-region are positively impacted by low local precipitation, and negatively by the low elevation of the terrain and poor coverage of the stormwater drainage system. According to Caprario and Finotti (2019), the C3 sub-region faces increasing pressure from urbanization, with disorderly expansion and low coverage (only 13%) of an undersized drainage network system characterized as absolute separator. The model of this region indicates the need to prioritize investment for the implementation of a stormwater drainage system. It is noteworthy that due to the low terrain elevation and the superficiality of the groundwater level, this region has many areas of recharge and outcrop of the aquifer. Another constant

observed in the region is the frequency of storm surge and erosion events, requiring careful planning and choice of coastal engineering works that can be implemented.

The low performance of the $MEIC_{C3}$ model suggests the need for a more detailed analysis of the environmental and anthropogenic variables considered. One of the hypotheses suggested by the authors is that there is subsidence process in this sub-region, considering the constant extraction of groundwater both by the local water supply company and by the local community itself.

5 CONCLUSIONS

The results highlight the potential of the proposed strategy to spatially modelling the flooding occurrence in coastal areas using information available in free and easily accessible online databases. The first results are very promising and show that the MEIC strategy can be a statistically robust and effective. In addition, the combination of statistical techniques and geospatial analysis has demonstrated a good capacity to explain the spatial distribution of the flooding points and their relationship with the hydrological, topographical, geological and anthropic characteristics present in each location.

As expected, the results showed limitations for modelling one of the three regions, probably due to the influence of an external factor, and it is not possible to identify consistent direct relationships, only some trends. In addition to primary function of the MEIC strategy, valuable information can also be obtained by analysing the distribution of classes for each influencing factor within their sub-regions. However, it is important to stress that the spatial datasets may be subject to error that may certainly affect the final quality of the results. In the case of higher quality input data unavailability (for example, increased accuracy and spatial resolution), the influencing factors data can be improved including validation in loco of the information. Another relevant characteristic to be considered for a better performance and precision of the strategy would be to include the accumulated precipitation of two to five days in advance, thus considering the soil moisture conditions.

The general results of the application of the strategy provide direct information that improves the understanding of the factors that influence the spatial distribution of the flooding points, allowing an easy comparison between different sub-regions. With 10 available explanatory factors, the best MEIC model can explain 76% of the distribution of flooding events, with an AICc of 41.858. The MEIC model with the worst performance can explain 40% of the flooding events, showing significant spatial autocorrelation in the residues, which reveals both the complexity of coastal flooding and the limitations of the strategy. The most novel and interesting finding of this study is that the relationships between environmental and anthropogenic variables and flooding events are not homogenous over space.

The strategy was able to reach the proposed objectives, presenting robustness and effectiveness of application, proving to be a potential approach for planning, development and integrated management of the coastal urban environment. This strategy can be adopted by the public managers, as well as by the academic community, as a way to subsidize decision-making, seeking socially and economically viable solutions, considering limited resources, in relation to the choice of protection measures and adaptation of previously built infrastructure.

We highlight in this paper a strategy based on socio-hydrological principles, which considers the population as an important part of the system, contributing to the observation, understanding and dissemination of phenomena in real places in the landscape where real people live. We emphasize that hydrology can be improved by reconstructing and studying the past, complementing temporal and spatial analyzes through human databases (social sphere), bringing essential contributions, not only, but mainly, when the conventional system has failed.

For future studies, and to take further advantage of the versatility of MEIC strategy, research efforts could be focused on including other factors of influence, for example, the process of local subsidence and coastal erosion. In addition, the geostatistical approach presented in this study can also be replicated in other developing nations, which lack accurate information and have limited financial resources for urban planning and management.

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Appendix A

Table A Characterization of the environmental and anthropogenic variables of each event and flooding site in the study area

Data	Latitude	Longitude	ID	N. flooding events	Sea level	Rainfall	Elevation	Hydrography	Stormwater Drainage	Land use	Soil type	Hydrogeology	Slope	Groundwater level
2013-03-10	-27.706209	-48.501654	1	1	61.55	81.80	9.29	No	No	Urban	Arenosols	Sedimentary	1.43	7.00
2013-03-10	-27.706297	-48.504472	2	1	61.55	81.80	7.75	No	Yes	Urban	Arenosols	Sedimentary	0.00	7.00
2013-06-01	-27.705508	-48.499568	3	1	53.45	26.41	5.59	No	No	Urban	Arenosols	Sedimentary	1.58	1.50
2013-06-01	-27.705438	-48.500037	4	1	53.45	26.41	4.78	No	Yes	Urban	Arenosols	Sedimentary	1.58	3.50
2013-06-01	-27.705187	-48.499874	5	1	53.45	26.41	4.64	No	Yes	Urban	Arenosols	Sedimentary	1.58	3.50
2013-06-01	-27.705241	-48.499161	6	1	53.45	26.41	5.25	No	No	Urban	Arenosols	Sedimentary	0.40	1.50
2013-06-01	-27.70556	-48.499304	7	1	53.45	26.41	5.50	No	No	Urban	Arenosols	Sedimentary	1.58	1.50
2013-06-01	-27.704741	-48.499269	8	1	53.45	26.41	4.64	No	Yes	Urban	Arenosols	Sedimentary	2.06	1.50
2013-06-01	-27.704196	-48.498577	9	1	53.45	26.41	4.64	No	Yes	Urban	Arenosols	Sedimentary	1.12	1.50
2013-08-04	-27.703319	-48.498114	10	1	75.34	13.71	4.64	No	No	Urban	Arenosols	Sedimentary	0.35	1.50
2014-01-03	-27.701302	-48.506591	11	1	52.00	34.04	5.35	No	No	Urban	Arenosols	Sedimentary	1.00	3.50
2014-10-31	-27.699575	-48.494125	12	2	60.09	0.50	4.64	No	Yes	Urban	Arenosols	Sedimentary	0.90	1.50
2014-12-28	-27.699575	-48.494125	13	2	56.49	22.09	4.64	No	Yes	Urban	Arenosols	Sedimentary	0.90	1.50
2015-02-14	-27.699233	-48.494697	14	2	70.25	61.72	4.64	No	Yes	Urban	Arenosols	Sedimentary	0.53	1.50
2015-03-08	-27.696727	-48.493279	15	1	49.98	1.27	4.64	No	Yes	Urban	Arenosols	Sedimentary	0.35	1.50
2015-03-08	-27.699233	-48.494697	16	2	49.98	1.27	4.64	No	Yes	Urban	Arenosols	Sedimentary	0.53	1.50
2015-03-22	-27.696688	-48.492766	17	1	96.56	0.25	4.64	No	Yes	Urban	Arenosols	Sedimentary	0.35	0.50
2015-04-22	-27.695048	-48.503992	18	1	71.63	15.47	6.54	No	No	Urban	Mangrove	Sedimentary	0.50	3.50
2015-07-15	-27.694805	-48.491817	19	1	70.00	16.00	4.64	No	No	Urban	Arenosols	Sedimentary	1.60	0.50
2015-07-15	-27.69419	-48.490931	20	1	70.00	16.00	4.64	Yes	No	Urban	Arenosols	Sedimentary	0.73	0.50
2015-07-24	-27.692207	-48.488341	21	1	56.16	66.78	4.46	No	Yes	Urban	Arenosols	Sedimentary	0.18	5.50
2015-08-15	-27.683700	-48.499518	22	1	51.00	0.00	4.72	No	No	Vegetation	Mangrove	Sedimentary	0.00	1.50
2015-08-15	-27.681154	-48.498169	23	6	51.00	0.00	9.32	No	Yes	Urban	Arenosols	Sedimentary	1.19	5.50
2015-08-15	-27.685047	-48.500219	24	1	51.00	0.00	13.62	No	No	Urban	Arenosols	Sedimentary	2.55	5.50

2015-08-15	-27.673468	-48.486542	25	6	51.00	0.00	9.32	No	Yes	Urban	Arenosols	Sedimentary	1.19	5.50
2015-08-15	-27.705538	-48.498675	26	6	51.00	0.00	9.32	No	Yes	Urban	Arenosols	Sedimentary	1.19	5.50
2015-08-15	-27.696705	-48.492641	27	1	51.00	0.00	6.61	No	Yes	Vegetation	Arenosols	Sedimentary	0.73	7.00
2015-08-15	-27.703297	-48.497484	28	6	51.00	0.00	9.32	No	Yes	Urban	Arenosols	Sedimentary	1.19	5.50
2015-08-15	-27.704719	-48.498641	29	1	51.00	0.00	9.45	No	Yes	Urban	Arenosols	Sedimentary	1.19	5.50
2015-08-15	-27.704174	-48.497947	30	6	51.00	0.00	9.32	No	Yes	Urban	Arenosols	Sedimentary	1.19	5.50
2015-08-15	-27.694782	-48.491176	31	1	51.00	0.00	11.56	No	No	Urban	Arenosols	Sedimentary	0.90	5.50
2015-08-15	-27.694167	-48.490288	32	1	51.00	0.00	9.42	No	Yes	Urban	Arenosols	Sedimentary	0.40	5.50
2015-08-15	-27.696665	-48.492126	33	1	51.00	0.00	4.17	No	No	Urban	Arenosols	Sedimentary	0.53	5.50
2015-08-15	-27.690705	-48.486805	34	1	51.00	0.00	12.05	No	No	Urban	Arenosols	Sedimentary	1.77	5.50
2015-08-15	-27.692184	-48.487692	35	6	51.00	0.00	9.32	No	Yes	Urban	Arenosols	Sedimentary	1.19	5.50
2016-03-03	-27.660078	-48.503318	36	8	59.76	51.55	1.43	Yes	Yes	Urban	Mangrove	Sedimentary	0.35	0.50
2016-03-03	-27.673492	-48.487177	37	1	59.76	51.55	11.83	No	No	Urban	Arenosols	Sedimentary	1.68	5.50
2016-03-25	-27.699211	-48.494061	38	8	62.30	86.34	1.43	Yes	Yes	Urban	Mangrove	Sedimentary	0.35	0.50
2016-03-25	-27.699553	-48.493487	39	8	62.30	86.34	1.43	Yes	Yes	Urban	Mangrove	Sedimentary	0.35	0.50
2016-09-15	-27.657056	-48.506796	40	1	100.61	1.80	3.14	No	Yes	Urban	Mangrove	Sedimentary	0.71	0.50
2016-09-15	-27.600998	-48.573614	41	8	100.61	1.80	1.43	Yes	Yes	Urban	Mangrove	Sedimentary	0.35	0.50
2016-09-15	-27.600633	-48.552715	42	8	100.61	1.80	1.43	Yes	Yes	Urban	Mangrove	Sedimentary	0.35	0.50
2016-09-15	-27.578052	-48.520057	43	8	100.61	1.80	1.43	Yes	Yes	Urban	Mangrove	Sedimentary	0.35	0.50
2016-09-15	-27.577139	-48.517101	44	8	100.61	1.80	1.43	Yes	Yes	Urban	Mangrove	Sedimentary	0.35	0.50
2016-09-15	-27.599096	-48.556033	45	8	100.61	1.80	1.43	Yes	Yes	Urban	Mangrove	Sedimentary	0.35	0.50
2016-09-15	-27.599093	-48.556396	65	8	100.61	1.80	0.81	No	Yes	Urban	Arenosols	Crystalline	0.71	5.28
2016-10-06	-27.652864	-48.524274	46	3	43.60	21.83	0.63	Yes	Yes	Mangrove	Mangrove	Sedimentary	0.73	2.22
2016-10-25	-27.652864	-48.524274	47	3	46.71	24.62	0.63	Yes	Yes	Mangrove	Mangrove	Sedimentary	0.73	2.22
2017-01-31	-27.590305	-48.515367	48	2	38.64	100.08	3.26	Yes	Yes	Urban	Mangrove	Sedimentary	2.74	2.85
2017-01-31	-27.590900	-48.505495	49	3	38.64	100.08	0.63	Yes	Yes	Mangrove	Mangrove	Sedimentary	0.73	2.22
2017-01-31	-27.587584	-48.504788	50	2	38.64	100.08	3.26	Yes	Yes	Urban	Mangrove	Sedimentary	2.74	2.85
2017-01-31	-27.455030	-48.400767	51	6	38.64	100.08	3.14	No	Yes	Urban	Cambisols	Crystalline	0.40	4.13

2017-01-31	-27.660058	-48.502743	52	6	38.64	100.08	3.14	No	Yes	Urban	Cambisols	Crystalline	0.40	4.13
2017-01-31	-27.434456	-48.397174	53	1	38.64	100.08	0.76	Yes	Yes	Urban	Arenosols	Crystalline	0.95	5.95
2017-01-31	-27.431175	-48.446251	54	6	38.64	100.08	3.14	No	Yes	Urban	Cambisols	Crystalline	0.40	4.13
2017-01-31	-27.509754	-48.470169	55	6	38.64	100.08	3.14	No	Yes	Urban	Cambisols	Crystalline	0.40	4.13
2017-06-05	-27.74421	-48.509086	57	6	52.53	43.43	2.32	No	Yes	Vegetation	Arenosols	Crystalline	0.40	5.52
2017-06-05	-27.432397	-48.456436	58	6	52.53	43.43	2.32	No	Yes	Vegetation	Arenosols	Crystalline	0.40	5.52
2017-06-05	-27.645727	-48.523698	59	6	52.53	43.43	3.14	No	Yes	Urban	Cambisols	Crystalline	0.40	4.13
2017-08-10	-27.600916	-48.553023	61	6	63.44	1.01	2.32	No	Yes	Vegetation	Arenosols	Crystalline	0.40	5.52
2017-08-20	-27.655326	-48.525330	62	6	64.95	25.91	2.32	No	Yes	Vegetation	Arenosols	Crystalline	0.40	5.52
2017-08-20	-27.600633	-48.552715	63	6	64.95	25.91	2.32	No	Yes	Vegetation	Arenosols	Crystalline	0.40	5.52
2017-08-20	-27.599096	-48.556033	64	6	64.95	25.91	2.32	No	Yes	Vegetation	Arenosols	Crystalline	0.40	5.52
2018-01-16	-27.437629	-48.401014	67	8	62.77	61.75	0.81	No	Yes	Urban	Arenosols	Crystalline	0.71	5.28
2018-01-16	-27.447993	-48.430342	68	8	62.77	61.75	0.81	No	Yes	Urban	Arenosols	Crystalline	0.71	5.28
2018-01-16	-27.438335	-48.410889	69	8	62.77	61.75	0.81	No	Yes	Urban	Arenosols	Crystalline	0.71	5.28
2018-01-16	-27.437746	-48.403140	70	8	62.77	61.75	0.81	No	Yes	Urban	Arenosols	Crystalline	0.71	5.28
2018-01-16	-27.422111	-48.430986	71	8	62.77	61.75	0.81	No	Yes	Urban	Arenosols	Crystalline	0.71	5.28
2018-06-15	-27.599099	-48.556397	72	8	84.75	0.00	0.81	No	Yes	Urban	Arenosols	Crystalline	0.71	5.28
2018-06-25	-27.645713	-48.523196	73	1	100.61	1.80	3.12	Yes	Yes	Urban	Acrisols	Crystalline	1.46	4.39
2018-06-25	-27.660058	-48.502743	74	1	100.61	1.80	0.82	Yes	Yes	Urban	Mangrove	Crystalline	0.53	3.04
2018-08-26	-27.578052	-48.520057	75	5	99.23	0.00	3.00	Yes	Yes	Mangrove	Mangrove	Crystalline	0.25	3.96
2018-08-26	-27.577139	-48.517101	76	2	99.23	0.00	0.00	Yes	No	Urban	Mangrove	Crystalline	0.50	2.45
2018-08-26	-27.660058	-48.502743	77	2	99.23	0.00	0.00	Yes	No	Urban	Mangrove	Crystalline	0.50	2.45
2018-09-03	-27.599099	-48.556397	66	8	61.03	90.00	0.81	No	Yes	Urban	Arenosols	Crystalline	0.71	5.28
2018-09-03	-27.587584	-48.504788	78	5	61.03	90.00	0.00	Yes	Yes	Mangrove	Mangrove	Crystalline	0.79	4.17
2018-09-03	-27.599628	-48.557876	79	5	61.03	90.00	3.04	Yes	Yes	Mangrove	Mangrove	Crystalline	0.25	3.96
2018-09-03	-27.577609	-48.524400	80	5	61.03	90.00	0.00	Yes	Yes	Mangrove	Mangrove	Crystalline	0.79	4.17
2018-09-03	-27.653118	-48.516584	81	1	61.03	90.00	3.45	No	Yes	Urban	Mangrove	Crystalline	1.43	3.41
2018-09-03	-27.688248	-48.510299	82	5	61.03	90.00	3.04	Yes	Yes	Mangrove	Mangrove	Crystalline	0.25	3.96

2018-09-03	-27.480386	-48.407489	83	5	61.03	90.00	0.00	Yes	Yes	Mangrove	Mangrove	Crystalline	0.79	4.17
2018-09-03	-27.446296	-48.397720	84	5	61.03	90.00	3.04	Yes	Yes	Mangrove	Mangrove	Crystalline	0.25	3.96
2018-09-03	-27.441306	-48.406171	85	5	61.03	90.00	3.04	Yes	Yes	Mangrove	Mangrove	Crystalline	0.25	3.96
2019-07-03	-27.660058	-48.502743	86	1	100.00	0.00	21.95	No	Yes	Vegetation	Arenosols	Sedimentary	0.18	3.34
2019-07-03	-27.645713	-48.523196	87	1	100.00	0.00	1.29	Yes	Yes	Urban	Acrisols	Sedimentary	1.29	4.92
2019-07-03	-27.599096	-48.556033	88	5	100.00	0.00	0.00	Yes	Yes	Mangrove	Mangrove	Crystalline	0.79	4.17
2019-07-03	-27.600633	-48.552715	89	5	100.00	0.00	0.00	Yes	Yes	Mangrove	Mangrove	Crystalline	0.79	4.17
2019-07-04	-27.452295	-48.399341	90	1	100.00	0.00	19.37	No	Yes	Vegetation	Arenosols	Sedimentary	0.64	2.21
2019-07-04	-27.455235	-48.401519	91	1	100.00	0.00	19.53	No	Yes	Vegetation	Arenosols	Sedimentary	0.35	3.02
2019-07-04	-27.465906	-48.463569	92	1	100.00	0.00	9.45	No	Yes	Vegetation	Arenosols	Sedimentary	13.60	6.73
2019-07-04	-27.444335	-48.501298	93	1	100.00	0.00	1.87	Yes	Yes	Urban	Mangrove	Sedimentary	0.56	6.80
2019-07-04	-27.448176	-48.430975	94	1	100.00	0.00	1.83	Yes	Yes	Vegetation	Mangrove	Sedimentary	0.00	6.85
2019-07-04	-27.446513	-48.398478	95	1	100.00	0.00	13.13	No	Yes	Vegetation	Arenosols	Sedimentary	2.06	2.21
2019-07-05	-27.599096	-48.556033	96	1	90.00	0.00	2.98	Yes	Yes	Urban	Arenosols	Sedimentary	0.00	3.55
2019-07-05	-27.578052	-48.520057	97	2	90.00	0.00	0.25	Yes	Yes	Urban	Mangrove	Sedimentary	0.40	6.93
2019-07-05	-27.577139	-48.517101	98	3	90.00	0.00	8.27	No	Yes	Urban	Arenosols	Sedimentary	1.00	3.34
2019-07-05	-27.660058	-48.502743	99	3	90.00	0.00	7.76	No	Yes	Urban	Arenosols	Sedimentary	2.37	4.19
2019-07-05	-27.645713	-48.523196	100	3	90.00	0.00	9.18	No	Yes	Urban	Arenosols	Sedimentary	1.00	3.46
2019-07-05	-27.599096	-48.556033	101	1	90.00	0.00	12.88	No	Yes	Urban	Arenosols	Sedimentary	0.35	3.25
2019-07-05	-27.600633	-48.552715	102	1	90.00	0.00	2.98	Yes	Yes	Urban	Arenosols	Sedimentary	0.00	3.55
2019-07-06	-27.43252	-48.457058	56	1	80.00	0.00	3.99	No	No	Vegetation	Arenosols	Sedimentary	0.18	7.21
2019-07-06	-27.645727	-48.523698	60	6	80.00	0.00	3.14	No	Yes	Urban	Cambisols	Crystalline	0.40	4.13
2019-07-06	-27.599096	-48.556033	103	2	80.00	0.00	0.59	Yes	No	Urban	Arenosols	Sedimentary	0.00	6.64
2019-07-06	-27.578052	-48.520057	104	1	80.00	0.00	2.99	No	Yes	Urban	Arenosols	Sedimentary	0.71	7.12
2019-07-06	-27.577139	-48.517101	105	2	80.00	0.00	0.59	Yes	No	Urban	Arenosols	Sedimentary	0.00	6.64
2019-07-06	-27.660058	-48.502743	106	2	80.00	0.00	0.25	Yes	Yes	Urban	Mangrove	Sedimentary	0.40	6.93
2019-07-06	-27.599096	-48.556033	107	2	80.00	0.00	2.09	No	No	Vegetation	Acrisols	Crystalline	0.18	7.64
2019-07-06	-27.600633	-48.552715	108	2	80.00	0.00	2.09	No	No	Vegetation	Acrisols	Crystalline	0.18	7.64

Appendix B

Table B Results of the statistical tests of parametric and non-parametric correlation between environmental and anthropic variables

Factors	Test	Factors									
		Sea level	Rainfall	Elevation	Hydrography	Stormwater drainage	Land use	Soil type	Hydrogeology	Slope	Groundwater level
Sea level	r	1.000	-0.545*	0.004	0.323*	0.101	-0.105	0.286*	-0.053	0.046	-0.142
	ρ	1.000	-0.402*	-0.280*	0.307*	0.100	-0.111	0.293*	0.018	-0.221*	-0.131
	τ	1.000	-0.307*	-0.201*	0.258*	0.084	-0.090	0.247*	0.015	-0.156*	-0.091
Rainfall	r	-0.545*	1.000	-0.280*	0.102	0.161	0.308*	0.069	0.444*	-0.072	0.012
	ρ	-0.402*	1.000	-0.232*	0.049	0.119	0.258*	0.046	0.408*	-0.081	-0.181
	τ	-0.307*	1.000	-0.173*	0.043	0.105	0.221*	0.045	0.357*	-0.059	-0.128
Elevation	r	0.004	-0.280*	1.000	-0.503*	-0.111	-0.342*	-0.408*	-0.460*	0.223*	0.033
	ρ	-0.280*	-0.232*	1.000	-0.634*	-0.170	-0.323*	-0.492*	-0.519*	0.306*	-0.039
	τ	-0.201*	-0.173*	1.000	-0.529*	-0.142*	-0.271*	-0.386*	-0.433*	0.187*	-0.031
Hydrography	r	0.323*	0.102	-0.503*	1.000	0.132	0.494*	0.760*	0.066	-0.142*	-0.201*
	ρ	0.307*	0.049	-0.634*	1.000	0.132	0.491*	0.749*	0.066	-0.244*	-0.202*
	τ	0.258*	0.043	-0.529*	1.000	0.132*	0.475*	0.722*	0.066	-0.206*	-0.168*
Stormwater drainage	r	0.101	0.161	-0.111	0.132	1.000	0.139	0.080	0.180	0.016	-0.047
	ρ	0.100	0.119	-0.170	0.132	1.000	0.137	0.061	0.180	-0.013	-0.060
	τ	0.084	0.105	-0.142*	0.132*	1.000	0.133*	0.059	0.180*	-0.011	-0.050
Land use	r	-0.105	0.308*	-0.342*	0.494*	0.139	1.000	0.400*	0.126	-0.124	-0.221*
	ρ	-0.111	0.258*	-0.323*	0.491*	0.137	1.000	0.369*	0.119	0.132	-0.262*
	τ	-0.090	0.221*	-0.271*	0.475*	0.133*	1.000	0.337*	0.116	0.101	-0.214*
Soil type	r	0.286*	0.069	-0.408*	**0.760***	0.080	0.400*	1.000	0.035	-0.097	-0.265*
	ρ	0.293*	0.046	-0.492*	**0.749***	0.061	0.369*	1.000	0.019	-0.152	-0.243*
	τ	0.247*	0.045	-0.386*	**0.722***	0.059	0.337*	1.000	0.018	-0.115	-0.188*
Hydrogeology	r	-0.053	0.444*	-0.460*	0.066	0.180	0.126	0.035	1.000	-0.166	0.271*
	ρ	0.018	0.408*	-0.519*	0.066	0.180	0.119	0.019	1.000	-0.157	0.254*
	τ	0.015	0.357*	-0.433*	0.066	0.180*	0.116	0.018	1.000	-0.133*	0.211*

Slope	r	0.046	-0.072	0.223*	-0.142	0.016	-0.124	-0.097	-0.166	1.000	0.094
	ρ	-0.221*	-0.081	0.306*	-0.244*	-0.013	0.132	-0.152	-0.157	1.000	0.014
	τ	-0.156*	-0.059	0.187	-0.206*	-0.011	0.101	-0.115	-0.133*	1.000	0.016
Groundwater level	r	-0.142	0.012	0.033	-0.201*	-0.047	-0.221*	-0.265*	0.271*	0.094	1.000
	ρ	-0.131	-0.181	-0.039	-0.202*	-0.060	-0.262*	-0.243*	0.254*	0.014	1.000
	τ	-0.091	-0.128	-0.031	-0.168*	-0.050	-0.214*	-0.188*	0.211*	0.016	1.000

r: Pearson test, ρ: Spearman's Rho test, τ: Kendall's tau test.
Bold and underlined characters represent the biggest trends identified by 3 statistical methods together.
* Statically significant trends at the 5% significance level.

Figures

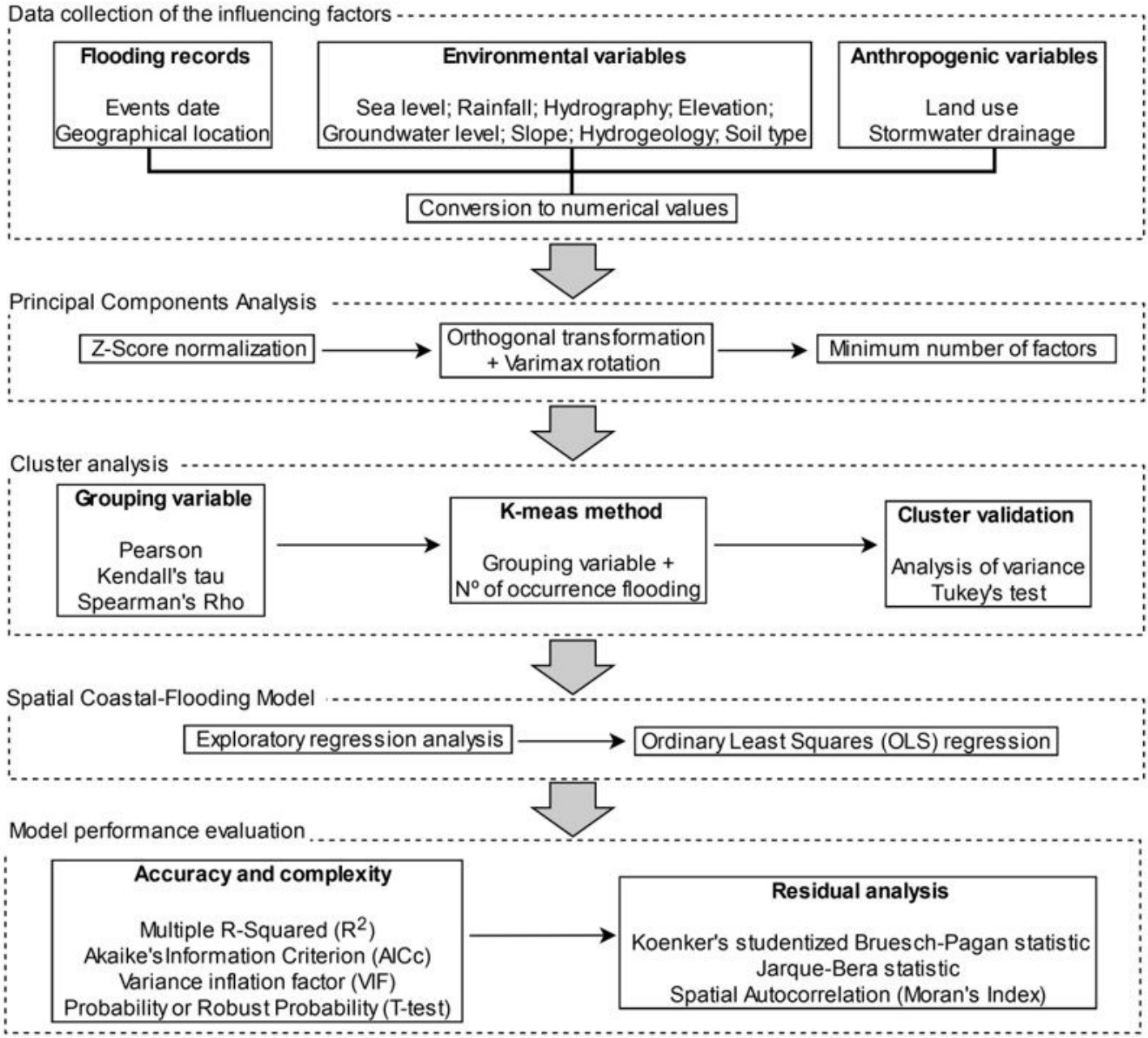

Figure 1

Conceptual framework of methodology

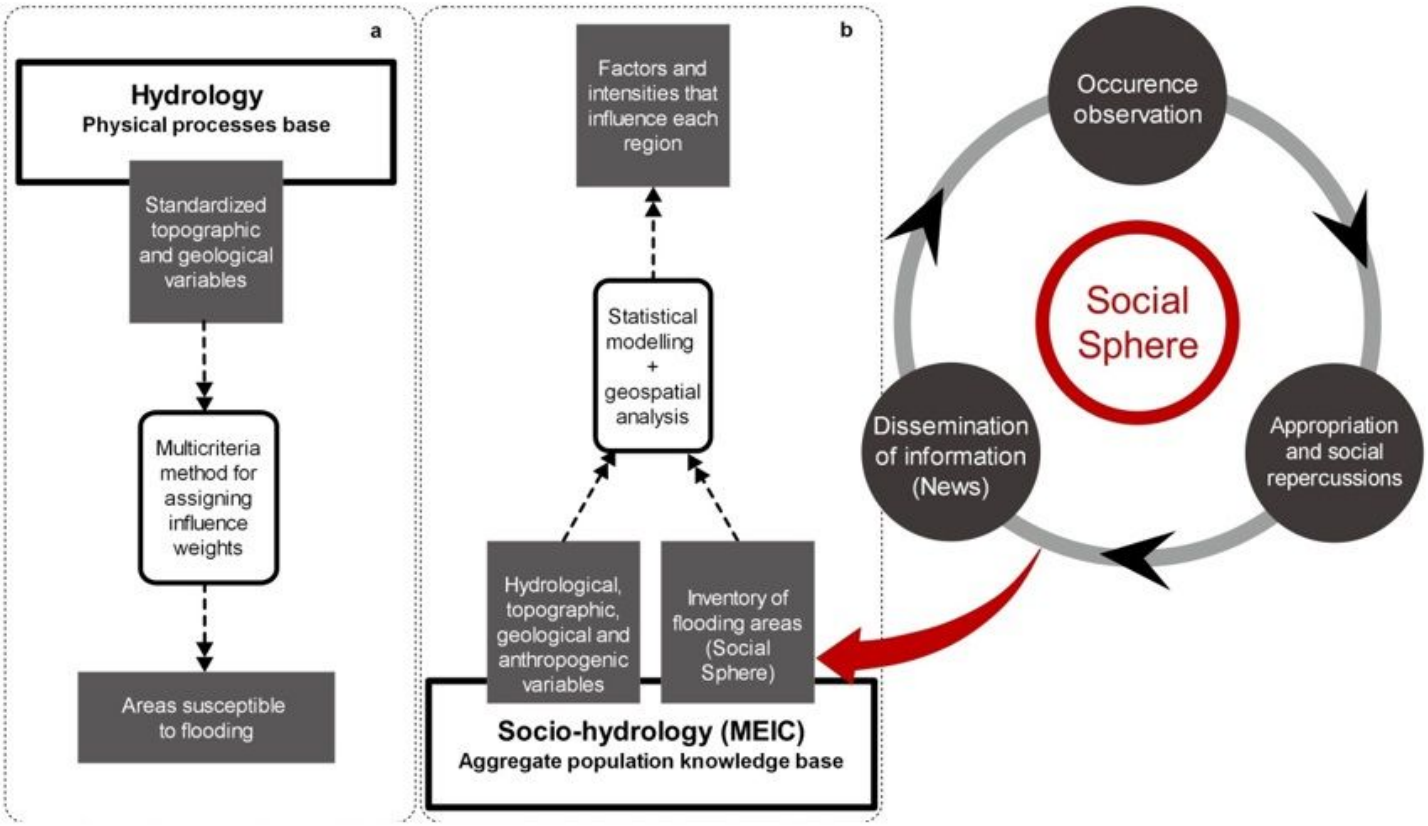

Figure 2

Flowchart diagrams of the spatial modelling. a) Hydrology modelling frame. b) Socio-hydrology modelling frame. In inverse modeling, the population knowledge is aggregated, and the main information is based on the social sphere looping (occurrence observation)

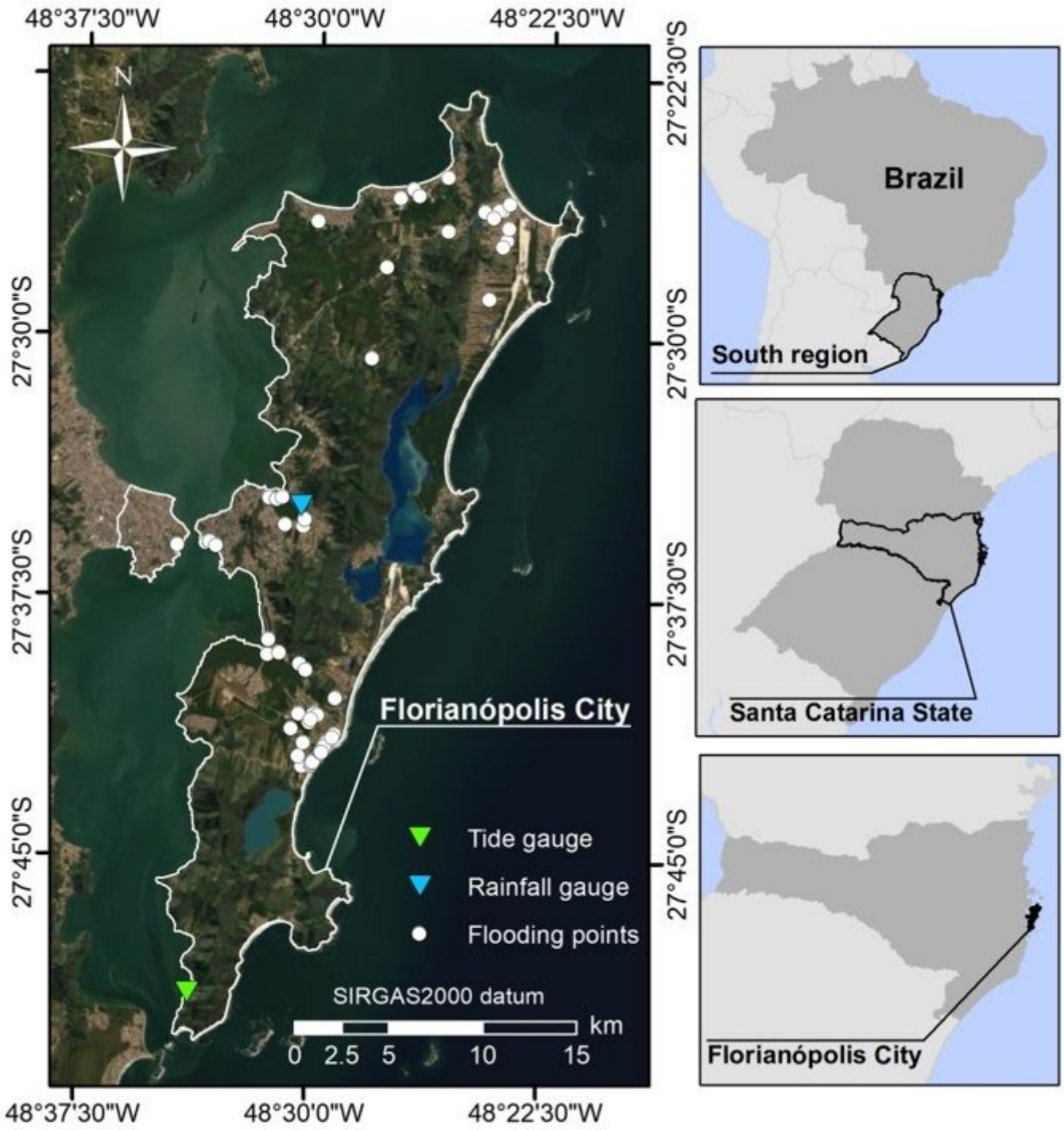

Figure 3

Location of Florianópolis City with locations of flooding occurrence

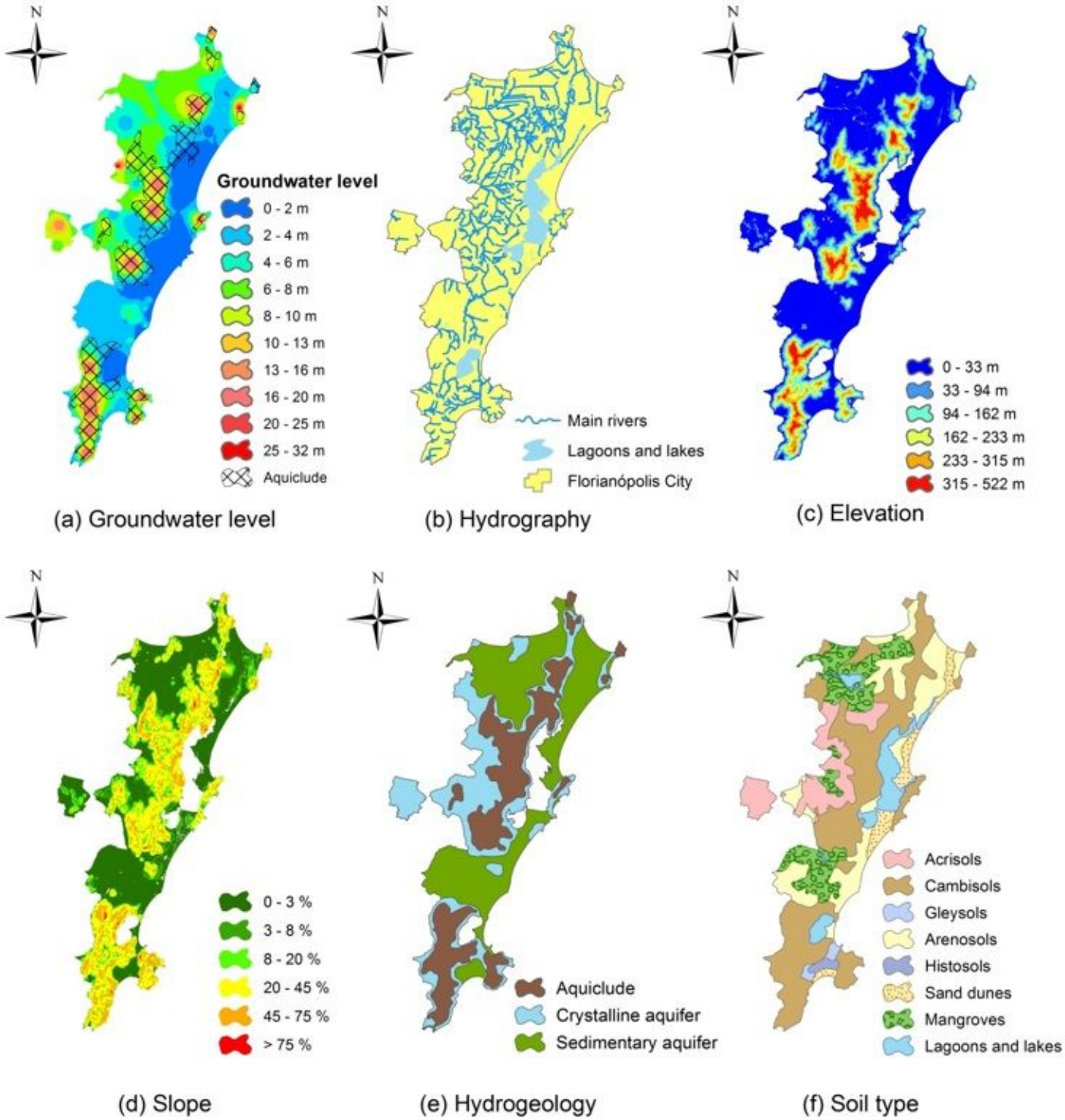

Figure 4

Spatial representation of factors groundwater level (a), hydrography (b), elevation (c) slope (d), hydrogeology (e), and soil type (f)

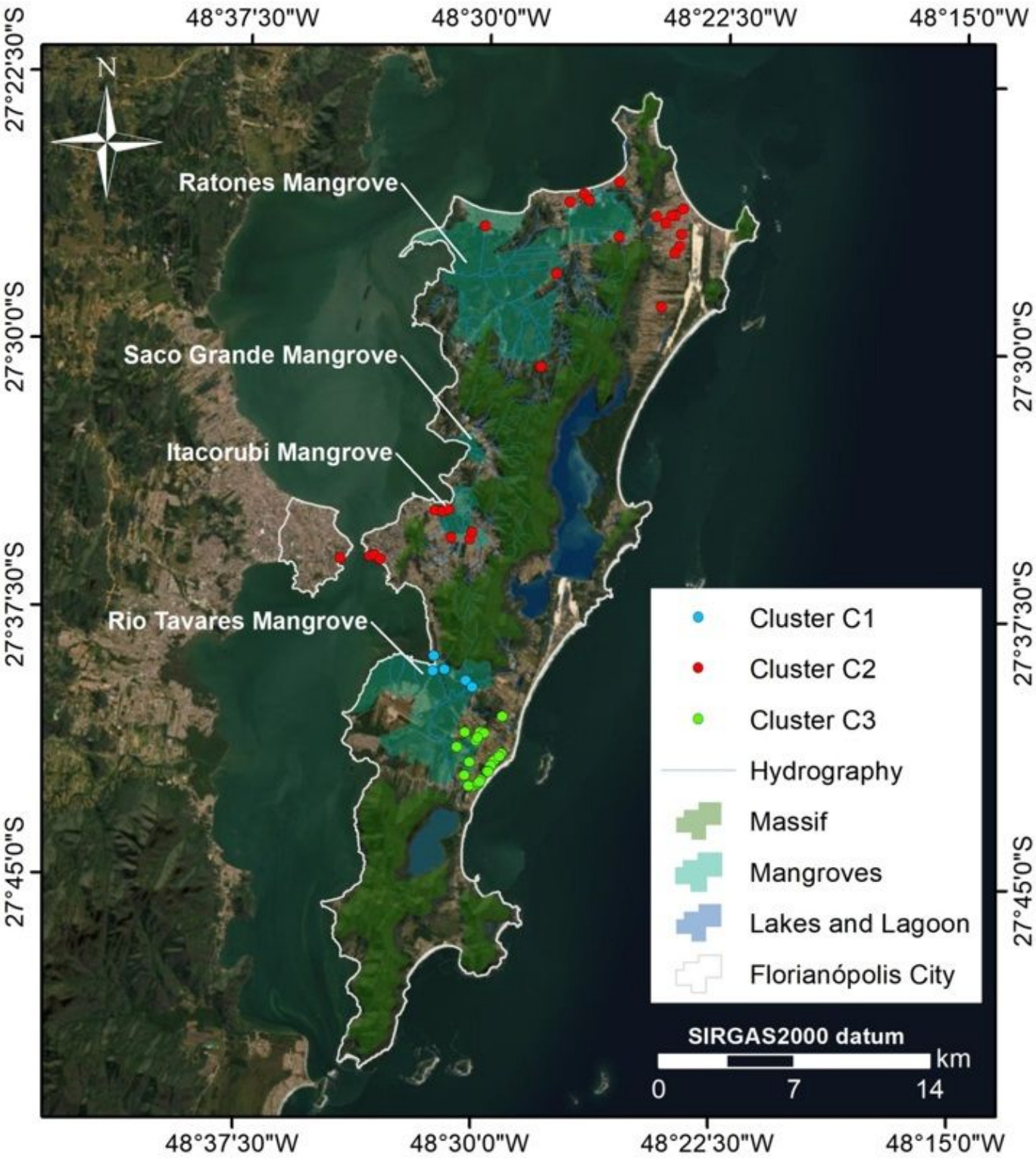

Figure 5

Flooding sites locations and classification according to the spatial constraint multivariate clustering (K-means)