Original Articles

Prediction of future risk of invasion by *Limnioperna fortunei* (Dunker, 1857) (Mollusca, Bivalvia, Mytilidae) in Brazil with cellular automata

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ARTICLE INFO

ABSTRACT

In South America, the presence of the non-native mollusc *Limnoperna fortunei* (Dunker, 1857) (Mollusca, Bivalvia, Mytilidae) in rivers and reservoirs may result in several impacts on the environment and economic activities. In a continental scale, the factors that most influence the dispersion of the species are anthropogenic vectors such as the movement of boats and people. Due to this, distribution models based solely on climatic variables often fail to predict the areas most subject to invasion, both spatially and temporally. An alternative to overcome this problem is the evaluation assuming the phenomenon as a complex system. In this paper, we have used a cellular automata model to predict the spread of the golden mussel in the Brazilian territory, on a temporal and spatial scale. We assume three parameters of interest: a) altitude b) characteristics of the river, and c) human population density. Transition rules were defined based on various considerations discussed in the article. The algorithm estimated satisfactorily the risk of invasion by *L. fortunei* to date (year of 2016), and the simulations for the years 2030 and 2050 predicted a high risk of invasion in north and northeastern Brazil. The increased risk of invasion predicted by the model for the next decades indicates that prevention and control measures should be applied immediately and this is of the utmost importance for the country to be able to comply with the #9 Aichi target.

1. Introduction

In South America, the presence of the mollusc *Limnoperna fortunei* (Dunker, 1857) (Mollusca, Bivalvia, Mytilidae) in rivers and reservoirs can eventually result in several environmental impacts such as the facilitation of growth of toxic cyanobacteria (Cataldo et al., 2012; Gazulha et al., 2012) and the rapid transformation in the composition of benthic communities, often favoring the presence of macro-invertebrates as Gastropoda, Oligochaeta and Hirudinea (e.g., Darrigran et al., 1998; Darrigran, 2002). In addition, this species can also cause negative impacts on hydropower generation activities (Darrigran et al., 2007; Darrigran and Damborenea, 2011; Nakano and Strayer, 2014), fish farms (Oliveira et al., 2014; Barbosa et al., 2016), and water withdrawals for human consumption (Darrigran and Damborenea, 2011; Pereyra et al., 2011). In some Brazilian municipalities the water supply faces serious problems due to fouling mussels in the raw water captation pipes (e.g., Brugnoli et al., 2005).

This small mollusk (~2–5 cm), popularly known as golden mussel, was introduced in South America (Argentina) in the early 90s, probably through the ballast water in ships from Asia (Pastorino et al., 1993). A few years later, in 1998, its presence was reported in Brazil (Mansur et al., 1999; Mansur et al., 2003; Oliveira et al., 2006). In the early twenty-first century, the golden mussel was already present in the second largest hydroelectric plant in the world, Itaipu, at the Brazil-Paraguay border, causing clogging of pipes and cooling systems (Pestana et al., 2010). In the following years, the invasion spread to the largest rivers of the Paraná basin at a velocity of about 240–264 km per year (Darrigran, 2002; Pareschi et al., 2008), arriving in the Triângulo Mineiro region (central Brazil) around 2011. By the year of 2014 the areas invaded by *L. fortunei* were mainly restricted to large rivers of the Paraná basin, in south-central Brazil, and to some areas of the Southeast Atlantic basin (see map in Barbosa et al., 2016). However, in 2015 its presence was reported 1500 km north of the invaded areas, in the Sobradinho reservoir on the São Francisco River (one of the largest

artificial lakes in the world, with a surface of 4214 km^2) (Barbosa et al., 2016; Almeida et al., 2016). Among the most reasonable causes for this long-distance dispersion (therefore called "jump dispersion") we highlight the probable shipping of golden mussel propagules in juvenile fish bags coming from infested areas or embedded in machinery used in engineering works (e.g., the construction of the São Francisco river transposition channel). Jump dispersion mediated by human activities is considered a primary way of spread for non-native organisms on a continental scale (Suarez et al., 2001). The frequency and distances of these long distance events are considered stochastic, difficult to be predicted, and can rarely be quantified (Higgins and Richardson, 1999). Thus, invasion prediction studies that do not take uncertainty into account can result in an under-prediction of the invaded areas, which reduces the effectiveness of plans to prevent and control new invasions (e.g., Beale and Lennon, 2012; Almpanidou et al., 2016; Elliott-Graves, 2016).

The simplest risk assessment protocols are mainly based on expert opinion and simple methods of statistical weighting (Branquart, 2007; D'Hondt et al., 2015). In general, when conservation objectives are based on research and professional assessments of specialists, the objectives exceed the limits imposed by current public policies (Svancara et al., 2005). In addition, the opinion of experts can be supported by paradigms that may not necessarily help in addressing the problem in hand (e.g., Pearce, 2015). Thus, models and simulations are interesting tools that enable the development of quantitative and transparent objectives for biodiversity conservation (Noss et al., 2012). In 2010, during the 10th Conference of the Parties to the Convention on Biological Diversity (CBD, 2010), the strategic plan for biodiversity was approved for the period of 2011–2020 (known as the "Aichi Goals"). Goal #9 of the Aichi plan proposes that by the year 2020 non-native invasive species and their introduction pathways are properly identified and are controlled or eradicated. Furthermore, the management of incoming routes must happen to effectively prevent the invasion episodes. In fact, preventive measures are recognized as the most efficient means of minimizing the introduction and, consequently, the impacts of invasive species (NISC, 2008; ANSTF, 2012). Moreover, they are important to mitigate the costs of control measures taken against already well-established non-native invasive species (Burnett et al., 2006; Kim et al., 2006; Olson and Roy, 2005). Among the tools to optimize existing prevention measures (inspections, quarantines, trade regulation, codes of conduct and education, among others), risk analysis models are the most attractive, since they have low operating costs and are relatively simple to implement (Peterson, 2003; Jiménez-Valverde et al., 2011; Uden et al., 2015).

Campos et al. (2014) mapped the environmental suitability for the golden mussel in the world through a climate-matching modeling approach (NAS, 2002). Since the algorithms used by the authors (Maxent, GARP, Mahalanobis, and Domain) quantify the realized climatic niche (e.g., Phillips et al., 2006) the projection of this niche in a new region will also represent the realized distribution of the species (Rodda et al., 2011). This is, in general terms, the major cause of overfitting in species distribution models that have many parameters, such as Maxent (Beaumont et al., 2005; Randin et al., 2006), i.e., when the model underestimates the areas of environmental suitability for a given species. In fact, the area of introduction of non-native species often reflects a greater extent of the fundamental niche than that found in native regions (Fitzpatrick et al., 2007; Kearney et al., 2008). To work around this problem Campos et al. (2014) used *L. fortunei* occurrence points from its native range and from invaded areas in an attempt to reach the maximum of the fundamental niche of the species in the projection. However, they used only bioclimatic variables (Hijmans et al., 2005) in the model development. This is a major problem, since most species have a restricted distribution in nature and these limitations could also be related to biotic factors. On a continental scale, biotic vectors related to human activities are the most important variables for the upstream dispersion of *L. fortunei* (Belz et al., 2012; Belz and Sebastiany, 2012).

Although important for downstream dispersion, in this case the dispersion is also favored by drifting larvae. On a local scale, the physicochemical conditions of water are also considered, while they can significantly influence the spatial distribution of the golden mussel (e.g., Darrigran et al., 2011). Thus, models that are based only on climate parity and does not take into account the stochastic jump dispersion (related to anthropogenic factors) can represent unrealistic scenarios of invasion underestimating the risk of invasion in various regions with idiosyncratic biotic/abiotic characteristics (Elliott-Graves, 2016). In addition, several studies show that niche shifting (and/or expansion) in invaded sites may be common for non-native organisms, which puts more doubt on the use of climate envelopes for the assessment of risk of invasion by alien species (Early and Sax, 2014; Guisan et al., 2014; Carlos-Júnior et al., 2015; Mazaris et al., 2015; Atwater et al., 2017).

An alternative to overcome this problem is the evaluation of this phenomenon from the concept of complex systems (Jesus and Kawano, 2002; Pearce and Merletti, 2006). The concept of complexity defines a collection of elements that make up a system with the freedom to act in a manner not always predictable, with interlocking action so that the action of an agent can change the context of other agents. The populations of living organisms, the brain, the financial market, the immune system, the spread of diseases, etc., are examples of complex systems. One of the precepts of these systems is that local rules, from the relations among the agents that make up the system, produce global effects. Some mathematical tools such as neural networks and cellular automata, are able to simulate these kinds of systems and have been used in several studies (e.g., Oliveira et al., 1991; Sirakoulis et al., 2000; Emmendorfer and Roberts, 2001; Peixoto et al., 2008). Cellular automata are discrete models in time and space whose evolutions are governed by simple rules (Schatten, 2007). Can represent complex real-world situations, such as the spread of diseases (Ahmed and Agiza, 1998; Doran and Laffan, 2005; Monteiro et al., 2007; Slimi et al., 2009), the growth dynamics of urban systems (Batty et al., 1999; Barredo et al., 2003), the spread of fire (Karafyllidis and Thanailakis, 1997; Albright and Meisner, 1999; Lopes et al., 2002), interspecific competition in plants (Silvertown et al., 1992), and the spread of invasive non-native species (Auld and Coote, 1981; Cole and Albrecht, 1999; Marco et al., 2002; Arii and Parrott, 2006; Huang et al., 2008; Gallien et al., 2010; Pukkala et al., 2014). Thus, we believe this tool is able to predict the risk of new invasions of golden mussel in Brazil taking into account the stochastic dispersion of this bivalve and avoiding the problems related to climate envelopes (e.g., Gallien et al., 2010). In this way, the aim of this study is to use a cellular automaton to simulate possible future scenarios of risk of invasion by the golden mussel (2030 and 2050) in Brazil based on environmental, topographical, and anthropogenic variables.

2. Material and methods

2.1. The cellular automata

A cellular automaton is a dynamic and discrete system in which space is represented by a regular and uniform grid with a given number of cells. Such cells display a finite number of states that change by following evolutionary rules (Gardner, 1970; Wolfram, 1982; Sipper, 2002; Wainwright, 2010; Kari, 2015). Time moves discreetly by local iterations, and the state of each cell can change at every unit of time, depending on deterministic or stochastic rules that are predefined in the system (Margolus, 1987; Ilachinski, 2001). The digital space in a cellular automata model consists of a rectangular grid composed of same-sized cells, each cell mapping an actual feature of that region. To modeling the dispersion of the golden mussel (see Fig. 1 for a flow chart), we assumed cells with a resolution of approximately 4.1 km at the equator (we believe that this is a realistic area of influence for the species) for the entire Brazilian territory, having three parameters of
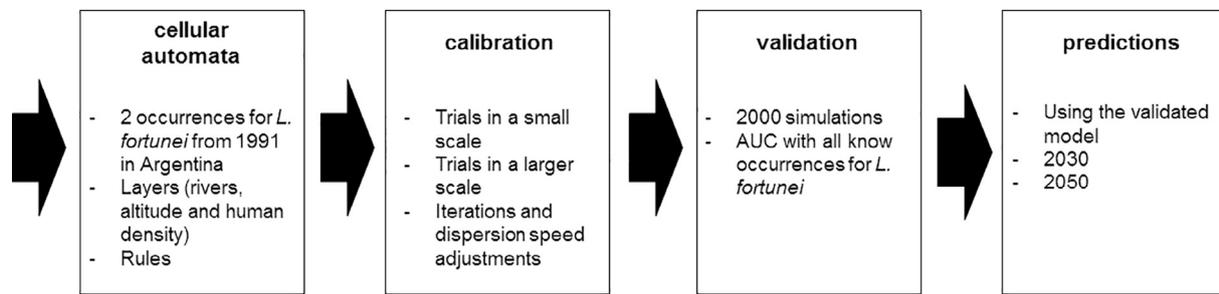
Fig. 1. Flow chart indicating the main phases of the invasion risk model for *Limnoperna fortunei* in Brazil, in three scenarios: years of 2016, 2030 and 2050.

interest: a) altitude (data from http://www.worldclim.org, Hijmans et al., 2005) (Osawa and Ito, 2015), b) river size and presence of waterways (waterway network data obtained from the Brazilian National Agency of Waterway Transportation – http://www.antaq.gov.br – and hydrology data from the National Water Agency – http://www.ana.gov.br) (e.g., Belz et al., 2012; Belz and Sebastiany, 2012), c) predicted population density for Brazil in 2015 (data from SEDAC – Socio-economic Data and Applications Center, http://sedac.ciesin.columbia.edu) (for a scheme, see the graphical abstract) (e.g., Belz et al., 2012; Belz and Sebastiany, 2012). We considered that the populational density pattern has not undergone any great significant pattern change in the last 30 years, so the same grid was employed for all calibration and prediction simulations. Cells of the grid containing river size data were divided in the following categories: navigable rivers, large non-navigable rivers, small rivers, medium rivers, land cells, and cells spanning areas invaded by the golden mussel. The altitude is an important parameter for the model, since in non-navigable rivers the downstream and upstream contamination dispersal occurs differently (Osawa and Ito, 2015). In these cases dispersal occurs at a higher rate when it happens downstream, compared to the upstream dispersal rate. Cells representing such cases contain data on terrain elevation, which ranges from 0 to ∼3000 meters relative to sea level. However, in navigable rivers such a distinction is unnecessary, because of the high traffic both downstream and upstream. Furthermore, it is known that the first golden mussel invasion events in South America advanced upstream of the entry waterways (Pastorino et al., 1993). Considering the importance of anthropic vectors in the spread of the golden mussel, the model also employed data on human population density in Brazil. In this case, the probability of the golden mussel dispersing to neighboring cells is positively correlated with human density, which has been divided into classes (1–30).

We employed the Moore neighborhood (Dragićević, 2010), in which each cell has eight scatter possibilities: right, left, down, up and the four diagonals. This choice was based on the necessity of using the diagonal scattering vectors, since the hydrographic mesh is complex and non-linear. If we were to use Neumann neighborhood (Neumann and Burks, 1966; Dragićević, 2010) (4 surrounding cells), many cells mapped as river would be out of dispersal route calculations.

Thus, we listed the bivalve main characteristics to guide the coding of spatial transit rules into the cellular automaton. The assumptions used as a starting point for the creation of the automaton rules are: a) the species' high rate of reproduction, b) the fact that living larvae are transported over great distances, c) the non-regulation of pesticide usage under Brazilian law, d) faster dispersion in navigable than in non-navigable rivers, e) differentiated upstream and downstream dispersion in non-navigable rivers, and f) the positive correlation between dispersion rate and human population density. Given these characteristics, the following rules of the automaton were established: a) if a cell is infected, all neighboring attainable cells have the same chance of being contaminated; b) if more than one cell is infected, then the probability of the next attainable cell to be infected is multiplied by the number of infected cells; c) random jumps are predicted to contemplate the spread strength through dispersal vectors; d) the probability of a attainable cell

to be contaminated by a neighboring cell is higher for navigable rivers than for smaller non-navigable rivers; e) the dispersion is faster downstream than upstream in non-navigable rivers; and f) the dispersion is faster in regions with high human population density.

The model considers the sum of the infected cell neighbors, i.e., the greater the number of infected neighbors, the more likely the evaluated cell to be also infected, which accelerates the rates of dispersion. Thus, the probability of being infected is directly related to the dispersion rate (Eq. (1)).

Dispersion probability = td∗dp∗jm∗nv (1)

Where td = river type, dp = population density, jm = downstream or upstream, nv = number of infected neighbors.

Each cell regarding the river type receives a value, defined in the model calibration phase, which can vary from 0 to 1. In the calibration phase was adopted annual dispersion speed of 240–264 km (Darrigran, 2002; Pareschi et al., 2008), to calibrate the amount of iterations relative to a year of the model in the three types of mapped rivers: navigable rivers, large rivers and medium and small rivers. The developed model considers two types of possible random jumps, whose objective is to contemplate the dispersion of the golden mussel by jumps that may be linked to human activities. In such a case, the model assumes that the chance of a jump to a limited distance is 98%, therefore, the chance of a jump to any of the national territory area is 2% (Suarez et al., 2001). The first, which most commonly occurs, would be the limited jump at a distance of up to ∼700 km and the jump can occur to the north, south, east or west. The jumps on a small scale are important because most of the dispersal events by leaps occurred in South America were in this way. The second jump, more unusual, but non negligible, would be the jump on a larger scale, i.e., a jump that can occur randomly throughout the study area (Brazil ∼8,500,000 km^2) (Appendix 1). For the algorithm to simulate this random jump, a mathematical model was created that is based on a "d", which is the largest relative distance that can be selected. For example, if the small jump is set to occur, it's jump ("y") will occur at a distance of ∼700 km away from the investigated cell, and the jump can occur to the north, south, east or west. Therefore, randomly selecting an "x" belonging to this radius, the probability of the jump to occur is given by "d = x/y". Thus, a number is randomly selected and the decision rule is based on comparing the random number with the expression:

$$\exp(-1/(2*0.16))*(d)^2 \qquad (2)$$

Where $d \in (-1,1)$, the value 0.16 was chosen so that the core would be centered on *0* and simulated values were between −1 and 1. Thus, the extent to which the distance increases, decreases the chance of large jumps to occur, as the core of the Gaussian distribution. It is noteworthy that if the golden mussel jump to an area with low population density, dispersion speed is close to zero.

The algorithm was implemented in Java JSE (Java Standard Edition) due to its good portability and versatility (Arnold et al., 2005).

2.2. Calibration and validation of the automaton

Calibrations were divided into three stages, the first phase characterized by trials on a small scale, at Paraguay and Paraná rivers. The automaton was being calibrated to correspond faithfully to the total time that the bivalves took to disperse the infected first point to the last point of these infected rivers. This first phase was extremely important to understand the interactions of variables, elevation, population density and size of the river, with the bivalves' dispersion speed. Upon completion of the first phase, the second phase aimed to perform validation on a larger scale, i.e., validate the algorithm on the map of Brazil considering the actual starting points of arrival of the golden mussel (Jacuí River in Rio Grande do Sul in 1998, Paraguai River in Mato Grosso do Sul in 1998 and Foz do Iguaçu in 2001). Each region invaded by the golden mussel had its specific test, analyzing the time it took the bivalves to disperse from his point of arrival in each region until its destination, that is, the last point where the presence of the golden mussel has been mapped in the region. Therefore, the second phase refined the influence of the river size, to estimate time dispersion the most realistic manner possible. The third and last phase had the aim to validate a simulation taking into account the interactions of regions concomitantly - instead of separate trials by regions, tests were carried out all at once, simulating as actually happened in the real scenario. In the last step we had minor adjustments, since the first trials gave good results.

After the construction and calibration of automata transition rules, the validation of the model was performed. The first invasion scenarios generated by the model were built to validate the rules applied to verify its effectiveness. For that were used only the first two points of contamination, which correspond to the La Plata River mouth in Argentina, where there was the first record of invasion by the golden mussel in South America in 1991 (Pastorino et al., 1993). From these two points 20 replicates were performed for 100 simulations (2000 simulations, speed of 400 iterations/year) corresponding to dispersion between 1991 and 2016. These data were compared with the occurrence points upgraded to the golden mussel, compiled by Oliveira et al. (2015) and Barbosa et al. (2016). These replicates were validated by calculating the area under the ROC curve (AUC) in the Maxent's command line (Manel et al., 2001; Phillips et al., 2006), and the Boyce index (Boyce et al., 2002; Hirzel et al., 2006) in the ecospat v2.2.0 package in R (R Development Core Team, 2010; Di Cola et al., 2017).

2.3. Simulations for 2030 and 2050

The simulations for 2030 and 2050 used the calibrated algorithm and were generated based on 20 replicates with 200 simulations and 400 iterations/year. The average risk of invasion was calculated for each Brazilian watershed (Amazon, Paraná, Uruguay, Tocantins, North Atlantic/Northeast, Southeast Atlantic, East Atlantic and San Francisco), in each of the three scenarios studied (current, 2030, and 2050), through the creation of 500 random points in the areas of rivers within each basin. We used the raster v2.5-8 package (Hijmans and Etten, 2012) implemented in R software (R Development Core Team, 2010). Since the data do not meet the basic conditions to test if there was a significant difference in risk over the years, parametric or nonparametric tests were not carried out (Gibbons and Chakraborti, 2005). The data were then interpreted in accordance with the trend shown by the means and standard deviations.

3. Results

After calibration the algorithm estimated satisfactorily the areas with risk of invasion by *L. fortunei*, showing an AUC value of 0.8119 ± 0.0031 (standard deviation, Fig. 2). Generally, AUC > 0.6 are considered indicative of high accuracy models (Swets, 1988). The Boyce index had an average value of -0.17 ± 0.02 (standard

deviation), which mean that presences are more frequent in low risk areas. This does not mean that the model is poor but only indicates a pattern of data distribution since the frequency of data in a given area does not represent the actual frequency of the species in the environment. Proximity to research centers (such as in the Pantanal) or hydroelectric power generation companies may create a collection bias that may be affecting the Boyce index.

The risk scenario built for year 2016 with two initial records from 1991 indicated a high risk of invasion for almost whole Paraná basin in Brasil. The model also indicated a possible contamination by jumping in the São Francisco River Basin, indicating the risk of contamination around the Três Marias reservoir. This result ensures reliability on the rules set for the model and therefore the models generated for the years 2030 and 2050.

The simulation for the 2030s showed an increase in risk of invasion areas, especially in northeastern Brazil, with a maximum standard deviation of 0.0718. The simulation for the 2050s indicated the appearance of areas with high risk of invasions in the northeastern and northern regions of Brazil (Fig. 3). The watersheds where the mussels have already established showed a stabilization trend in the risk of invasion in the future scenarios, while the basins that are currently free of the presence of *L. fortunei* present increased risk to the year 2050 (Fig. 4). The reliability of the projections to 2030 is higher in areas currently invaded, as can be observed in standard deviation values (Fig. 5). The results also indicate that the predictions becomes less certain as larger the prediction time, as we can see in the variance values for 2030 and 2050 (Fig. 5).

4. Discussion

One of the main aspects of the use of predictive models to subsidy objective public policy is the understanding that all model used in simulations is subject to errors (Edwards and Fortin, 2001; Barry and Elith, 2006; Hartley et al., 2006). In the results herein presented for current time, the areas of predicted risk omit some sections of invaded rivers (type I error – omission), and indicate areas at risk of invasion in places that still there is no record of the species (error type II – commission). However, high-risk prediction for highly infested rivers in the present day (Paranaíba, Tietê, Grande, among others) shows the enormous importance of this predictive model for the development of more effective control measures for this species.

In some situations, the model could present a better predictive capacity if it were possible to obtain reliable data from some human activities, such as fish stocking (as is the case of the invaded areas in Middle São Francisco River). Since there are no reliable data sources for obtaining this information, they were not entered into the model. The fish stocking activity has grown dramatically in Brazil in recent years (Agostinho et al., 2010; Lima Junior et al., 2012; Barbosa et al., 2016) and it might be considered the main cause behind the invasion of the Middle São Francisco River through larval transport from the bags of fingerlings, thus allowing a high pressure of propagules (Lockwood et al., 2005). Added to the fact that the significant production of fingerlings in the sub-basins of the Tietê, Grande and Paranaíba rivers (in the Paraná basin, southeast Brazil) provide animals for various fish stocking projects across the country, including North and Northeast regions. The golden mussel has invaded these regions years ago, where the bivalves cause many problems in water systems, fish farming and hydroelectric plants (Mansur et al., 1999; Mansur et al., 2003; Oliveira et al., 2006; Belz et al., 2012; Belz and Sebastiany, 2012). Thus the use of fingerlings originating from these regions to increase the fish population in natural reservoirs or fish farms can function as an important route of golden mussel introduction, particularly for basins unconnected to infested regions. Moreover, this suggest that new cases of jump dispersion can happen at any time in northern and northeastern Brazil, including the Amazon, where fish stocking projects with non-native species are encouraged by government policies (Pelicice et al.,
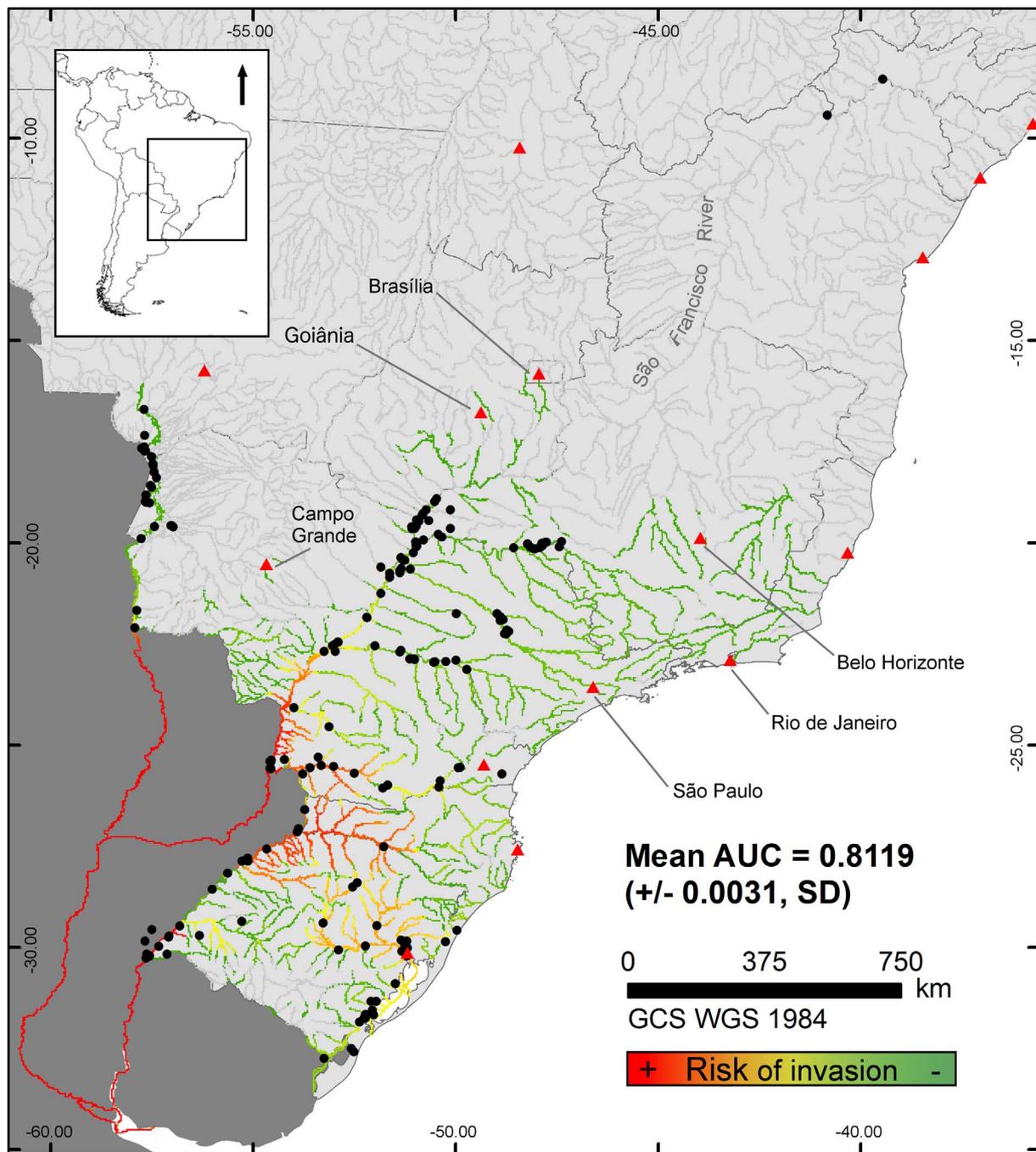
Fig. 2. Invasion risk scenario for the year 2016 based on two 1991 occurrence records generated by the average of 20 replicates of 100 simulations (with speed of 400 iterations/year). The black dots represent the current occurrence of points of *Limnoperna fortunei* in Brazil. The state capitals are represented by red triangles. The scale ranges from 0 (green, low risk of invasion) to 1 (red, high risk of invasion), which means the probability of presence or the risk of invasion. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2014; Padial et al., 2016). Our risk model indicates a high risk of invasion of the Amazon basin in the decade of 2050 and this scenario can be worst if we consider the fish stocking activities. In fact, the invasion of the Amazon basin by the golden mussel has already been discussed and is expected (Boltovskoy et al., 2006). The invasive non-native Bivalve *Corbicula fluminea*, for example, is already well established in the Amazon basin (Beasley et al., 2003; Santana et al., 2013).

In some cases, the 2016 model suggests invasion risk in areas that have no record of the species, which indicates type II errors (commission). In some cases, as the exorheic rivers of the East Atlantic watershed, the planktonic larvae of *L. fortunei* are probably flushed into the sea and the absence of lentic waterbodies is also a limiting factor for

an infestation. For most of these cases there is no guarantee that the species is really absent, since many stretches of rivers are not actively monitored and often the invasion events are only reported when the invasion process is already well advanced. Indeed, new cases are frequently reported (e.g., Silva et al., 2016). The basin of the Paraíba do Sul River, also indicated by the model generated for the year 2016 as a possible invasion region, has no recorded occurrence for *L. fortunei*. However, this basin does not have an active invasive species monitoring system. This basin has an area of ~56.500 km^2, covering regions of three Brazilian states with great economic importance: São Paulo, Minas Gerais and Rio de Janeiro. The results presented by the model and the implementation of river connection systems indicate that the
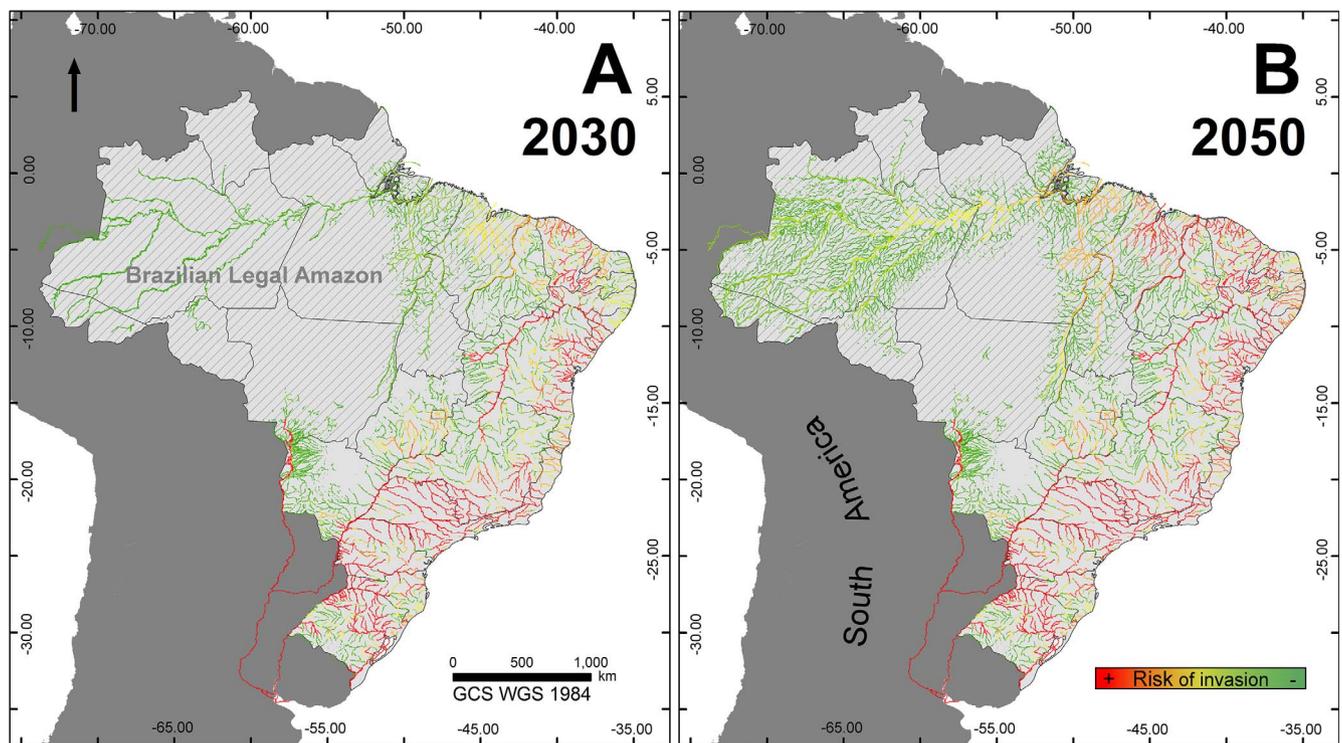
Fig. 3. Mean future scenarios generated by 4000 random simulations of the model constructed based on occurrence records from 2016 for *Limnoperna fortunei*. A) 2030s and B) 2050. Crosshatched areas indicates the limits of the Brazilian states that have the Amazon biome (Brazilian Legal Amazon). The scale ranges from 0 (green, low risk of invasion) to 1 (red, high risk of invasion), which means the probability of presence or the risk of invasion. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

spread of the golden mussel can occur rapidly in these regions if monitoring measures are not implemented. In some cases, despite the risk prediction, the establishment of *L. fortunei* cannot happen. In 2015, for example, there was a rupture of a mine tailings dam that released billions of liters of tailings mud from mining activities on the Doce River (southeastern Brazil), which traveled hundreds of kilometers to the sea (e.g., Escobar, 2015; El Bizri et al., 2016; Garcia et al., 2016; Neves et al., 2016; Fernandes et al., 2016). Although golden mussels are relatively tolerant to contaminants, the presence of mud and heavy metals through the river may adversely affect the development of filter-feeding organisms because the increased water turbidity is a detrimental factor for the survival of adults and larvae (Morton, 1975; Deaton et al., 1989; Ricciardi, 1998; Pareschi et al., 2008; Mackie and Claudi, 2010).

The model did not take into account the presence of water transposition systems that should be in full operation in 2018 in the northeast Brazil. These channels can enhance the dispersion of the golden mussel already this decade to the Eastern Atlantic river basin aggravating the drought situation that this region has been experiencing for decades (e.g., Marengo et al., 2016). Individuals of *L. fortunei* were identified on the north axis of the transposition system in the São Francisco River (Barbosa et al., 2016). Moreover, the model does not take into account the presence of fish farming and stocking activities, identified as one of the most efficient ways to carry live larvae to distant sites. Assuming that none of these activities are under efficient monitoring actions, control and inspection, we can say that the forecast models for 2030 are conservative and could suffer significant errors of submission. Another important point to note is that the models were created based on current boat traffic, population density, as well as actual rivers and basins connections. Possible changes in river connections, new jump infections (especially by fish farming and stocking activities), and population growth in some regions could accelerate the invasive processes significantly. In addition, the model was generated using only Brazil data (population densities and boat traffic by

waterways), however the transboundary basins can be contaminated at any time by neighboring countries such as Peru, Colombia, Ecuador, Venezuela, Guyana, Suriname and Bolivia. On the other hand, also, containment activities, either by sanitary barriers, surveillance strategies, management techniques, etc., may also contribute to the reduction of the risk predicted by the model for the years 2030 and 2050.

Although the anthropic variables are of great importance on a continental scale, on a smaller scale physicochemical properties of water are extremely dynamic and important to predict invasions and the possible consolidation of the invasion. The cellular automata model presented in this paper takes into account only the physical characteristics of the environment in a coarse resolution. It would be impracticable to use physicochemical characteristics of all Brazilian rivers given the great extent of the territory and the scarcity of the available data. In this sense, risk indices that contemplate the local dynamic variation of the systems are also important. In conjunction with the dynamic environmental model presented here, these indices can serve as good tools for the management, prevention and control of non-native invasive aquatic species, working on a local scale and in a more direct and effective way. The index proposed by Ferreira et al. (2015) (available at www.cbeih.org/indice) is able to merge limnological variables and dispersion vectors, although it is unable to quantify the time required for an area to be invaded. In a nutshell, this index tells which areas may or may not be invaded by the mussel in a high spatial resolution. Therefore, we suggest that this index is a complementary tool to the cellular automata presented in this paper and vice versa. Thus, it is expected that the addition of modeling tools and risk indices will assess, dynamically, risks of new areas being invaded by *L. fortunei*, while contemplating the invasion chronologically. In this way, we suggest the use of this protocol as a management tool, enabling the identification of priority regions for the prevention and control actions.
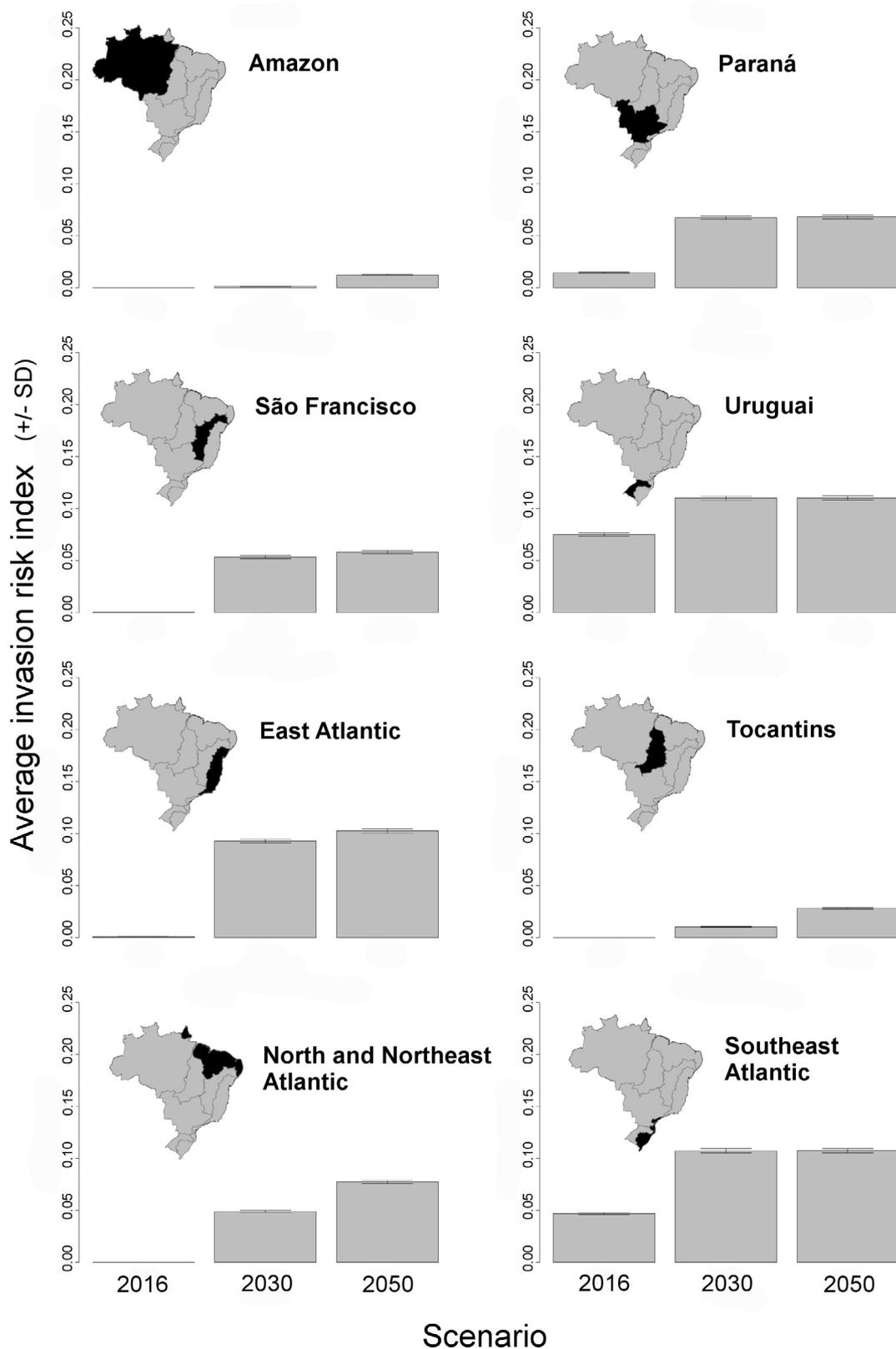
Fig. 4. Average risk of invasion for every Brazilian watershed, for the current scenario, 2030, and 2050.

5. Conclusion

The cellular automata model satisfactorily estimated the time and regions invaded by the species to the present day, corroborated by actual records. Therefore, this tool seems very promising for the management of invasive species, especially the golden mussel, allowing the establishment of priority areas for inspection, and guiding actions of control. In addition, the model allows the determination of the river stretches that would be key for the rapid spreading of the species, thereby reducing operational and environmental costs. In view of the
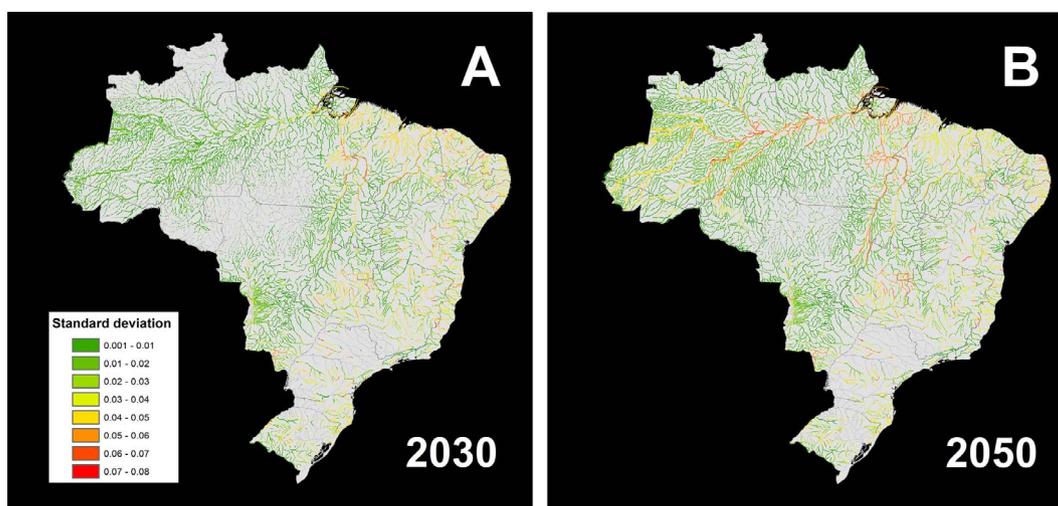
Fig. 5. Maps showing the standard deviation around the mean risk of invasion by *Limnoperna fortunei* constructed by using a cellular automaton for the period of A) 2030 and B) 2050.

imminent invasions in almost all Brazilian basins as pointed out by the model are indispensable the implementation of strategic actions involving companies, government, and society in general, so that all contribute to less impactful and more effective mechanisms to control the dispersion of this non-native invading organism. The increased risk of invasion predicted by the model indicates that prevention and control measures should be applied immediately. Otherwise Brazil runs the risk of not complying with what was agreed in the framework of the Aichi meeting.

Acknowledgement

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2018.01.005.

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