Improving the Generation of Earthquake Risk Models Using Evolutionary Algorithms tempered by Domain Knowledge

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***Abstract*—Earthquake Risk Models describe the risk of occurence of seismic events on a given area based on information such as past earthquakes in nearby regions, and the seismic properties of the area under study. These models can be used to**

Recently, Evolutionary Computation has been used to learn risk models using purely past earthquake occurrence as training data. While the results were promising, we believe that a much better model could be learned if domain knowledge, such as known theories and models on earthquake distribution, were incorporated into the Evolutionary Algorithm's training process.

In this work we approach this idea by improving former methods in two ways: (1) We modify the genome representation of a model from an area-based representation to an earthquake representation, and (2) we use known methods from seismology (such as the Omori-Utsu formula) to refine the candidates generated by the GA.

We analyze the contributions from each of these modifications using the methodologies described in the Collaboratory for The Study of Earthquake Predictability (CSEP), and compare their performance with (XXX method and YYY method). Our results indicate that (XXX result, YYY result)

1. Introduction

Earthquakes may cause soil rupture or movement, tsunamis and more. They may cause great losses and that can be explicit by some examples, such as the earthquakes in Tohoku (2011) and Nepal(2015). To be able to minimize the consequences of these events, we look to create forecast earthquake occurences models. Hence the characteristics that most influence the earthquakes events may vary both in time and place, these methods should be to adapt their behavior to be able to forecast earthquakes events which reflects well the reality.

This project aims to obtain a better method, based in improvements to the GAModel [1], a statistical method of analysis of earthquakes risk using the Genetic Algorithm technique (GA). Two ideias are proposed for this. The first one, is to change the candidate solution representation. By that, we objective to make the GAModel more specialized, focusing only on areas on which earthquakes happened already in a near past. This will lead to a faster convergence, once the amount of parameters is smaller and consequently, the search space gets smaller.

Formulated on this idea, we propose the ReducedGAModel. Its genome only has information of areas that already had occurences in the past. This helps the method to converge gets faster, by minimizing the number of parameters the method has to deal with.

The other ideia is based on the assumption that earthquakes cluster in both space and time, and the we want associate the Genetic Algorithm technique (GA) with a some empirical laws, such as the modified Omori law. First, the background intensity (the independent earthquakes or mainshocks), which is a function of the space, is forecasted using the GA. Then, we use some empirical laws to obtain the dependent earthquakes (aftershocks) for a specific time interval.

The Emp-GAModel is the method proposed that incorpores some geophysical knowledge. It is a hybridization of the models generated by the GAModel with the these empirical laws, see Section 3.

Finally, there is the Emp-ReducedGAModel. This method is a combination of the two ideias. Therefore, it also performs a hybridization of models with the group of empirical law. Though, for this method, the models are generated by the ReducedGAModel method and not by the GAModel.

The forecast models produced by those methods and the ones produced by the GAModel were all analyzed using likelihood tests, namely the L-test, the N-test and the R-test, as suggested by Regional Earthquake Likelihood Model (RELM) [2].

For developing the methods and to be able to compare them we used the earthquake catalog from the Japanese Meteorological Agency (JMA), using event data from 2005 to 2010.

This paper is organized as: in Section 2reviews applications of Evolutionary Computation in the context of seismology research. The next Section,Section 3, we give a details of each of the forecast proposed covering the Collaboratory for the Study of Earthquake Predictability (CSEP) framework and the empirical laws. In Section 4, we give the description of the tests proposed in [3]. After that, in 5, we define the target areas used for the experiment and the data from the JMA; we clarify the design followed during the experiments and how ew compared the forecast models derived from our methods. Finally, we show the results and conclude this work in 6 and 7.

2. Evolutionary Computation for Earthquake Risk Analysis

In this section we will briefly discuss some reports of the application of Evolutionary Computation and related method for Earthquake Risk Analysis.

The usage of Evolutionary Computation in the field of earthquake risk models is somewhat sporadic. Zhang and Wang [4] used Genetic Algorithms to fine tune an Artificial Neural Network (ANN) and use this system to produce a forecast model. Zhou and Zu [5] also proposed a combination of ANN and EC, but their system only forecasts the magnitude parameter of earthquakes. Sadat, in the paper [6], follows the idea oF Zhou and Zu, aiming to predict the magnitude of the earthquakes in North Iran, but in this case, he used ANN and GA.

Some sismological models were developed aiming to estimate parameter values by using Evolutionarry Computation. For example, Evolutionary Computation was used to estimate the peak ground acceleration of seismically active areas [7], [8], [9], [10]. Ramos [11] used Genetic Algorithms to decide the location of sensing stations and Saeidian [12] made a comparation in performance between the GA and Bees Algorithm to decide which of those techniques would performe better when chosing the location of sensing stations. Nicknam et al. [13] and Kennett and Sambridge [14] used evolutionary computation to determine the Fault Model parameters of a earthquake.

3. The Forecast Models Using Genetic Algorithm

All forecast models proposed in this paper are based in the Collaboratory for the Study of Earthquake Predictability (CSEP) framework.

Each individual has its own representation of the framework based on different perceptions of what are the best aspects of the framework.

The population is trained on earthquake event data for a training period, which is anterior to the target test period. After completing the evaluation limit, the best individual is chosen to be the final forecast.

3.1. 1-year Models

The CSEP framework, a forecast model uses a gridded rate forecast [15], one common format in the literature. For this format a geographical region is divided in sections, bins, during a start date and an end date. The forecast will estimate the number (and sometimes the magnitude) of earthquakes that happens in this target region, during the target time interval. For this study we considered the target time interval of one year [1].

Large and independent earthquakes, also known as mainshocks, are followed by a wave of others earthquakes, the aftershocks [16]. Hence there is no physical measurement to identify mainshocks and its aftershocks [16], we divided the forecast models in two groups: the ones that only forecasts mainshocks and those that forecast both mainshocks and aftershocks.

Both classes forecast earthquakes with magnitude greater than 3.0 for every scenario proposed, with a binning of 0.1, here named as cells to avoid conflicts with the location bin. That results in magnitude cells of [3.0, 3.1), [3.1, 3.2), until [9.9, 10). That was the only declustering procudered used for the all methods.

3.2. Genome Representation

In the GAModel each individual represents an entire forecast model. Each gene of the individual is a real value, corresponding to one bin in the desired model. The values are sampled from the interval [0, 1). These real values are converted to a integer forecast, we use the same modification of the Poisson deviates extraction algorithm used for the GAModel [1].

In the ReducedGAModel, each individual is a list of a subregion of the forecast model. This list initially is a refers to bins where earthquake events happened in the past. During the develop of the ReducedGAModel, the list may refer to positions that never had occurrences before. Each element of the list, a gene, also contains one real value between [0,1). In the initial population, this real values are sampled from a uniform population. When needed, every real value is converted to a integer forecast, as in the GAModel [1].

To generate the forecast model we need to do an intermediate step. We map every location from the list with a bin in the forecast map.

The genome size is usually smaller than the one used in the GAModel and the Emp-GAModel, once the amount of subregions where earthquakes with magnitude above 3.0 happened for any given area is smaller then the total number of genes of the individual.

The Emp-ReducedGAModel and the Emp-GAModel differs only from the ReducedGAmodel and from the GAmodel, respectively, by the use of equations after the forecast is provided. This means that the theirs genome representation are the same as the GAModel and the ReducedGAModel,correspondingly.

For all methods, the genome is a real valued array X, where each element corresponds to one bin in the desired model (the number of bins n is defined by the problem). Each element $x_i \in X$ takes a value from $[0, 1)$. In the initial population, these values are sampled from a uniform distribution. For more details of the genome represatation, please refer to [1].

3.3. Fitness Function

All the methods use the log-likelihood value, for the fitness function. The fittest individual among all the others, is preserved in the next generation, to make the solution of one generation as good as the its last generation. The bins, a gene of the genome representation, b_n, define the set β and n is the size of the set β:

$$\beta := b_1, b_2, ..., b_n, n = |\beta|. \tag{1}$$

The probability values of the model j, expressed by the symbol Λ, is made of expectations λ_i^j by bin b_i. The vector is define as:

$$\Lambda^j = \left(\lambda_1^j, \lambda_2^j, \ldots, \lambda_i^j\right); \lambda_i^j := \lambda_i^j(b_i), b_i \in \beta \tag{2}$$

The vector of earthquake quantity expectations is defined as: earthquake by time. The Ω vector is composed by observations ω_i per bin b_i, as the Λ vector:

$$\Omega = \left(\omega_1, \omega_2, \ldots, \omega_i\right); \omega_i = \omega_i(b_i), b_i \in \beta \tag{3}$$

The calculation of the log-likelihood value for the ω_i observation with a given expectation λ is defined as:

$$L(\omega_i|\lambda_i^j) = -\lambda_i^j + \omega_i \log \lambda_i^j - \log \omega_i! \tag{4}$$

The joint probability is the product of the likelihood of each bin, so the logarithm $L(\Omega|\Lambda^j)$ is the sum of for $L(\omega_i|\lambda_i^j)$ every bin b_i:

$$\begin{aligned} L^j = L(\Omega|\Lambda^j) = \sum_{i=1}^{n} L(\omega_i|\lambda_i^j) \\ = \sum_{i=1}^{n} -\lambda_i^j + \omega_i \log \lambda_i^j - \log \omega_i! \end{aligned} \tag{5}$$

The fitness function is a coded version of the equation 5. It uses the probabilities of the bins of each individual of model for the λ values.

3.4. Evolutionary Operators

Both the GAModel and the Emp-GAModel use a combination of operators made available by the Distributed Evolutionary Algorithms in Python (DEAP) [17]. We used the One Point Crossover for the crossover operator, the Polynomial Bounded Mutation for the mutation operator and for selection, we used Tournament selection and Elitism. The parameters are described in the Table 1.

For the ReducedGAModel and the Emp-ReducedGAModel, the only different operator is the mutation fuction. We use a simple mutation operator which samples entirely two new values, both sampled from uniform distributions. The first, is a new real value from [0,1) and the seconde one, a new integer value from [0,X), where X is the maximum length of the genome. For the parameters see Table 2.

TABLE 1. PARAMETERS USED IN GAMODEL AND EMP-GAMODEL

Population Size	500
Generation Number	100
Elite Size	1
Tournament Size	3
Crossover Chance	0.9
Mutation Chance (individual)	0.1
Polynomial Bounded parameters	eta = 1, low = 0, up = 1

TABLE 2. PARAMETERS USED IN GAMODEL AND EMP-GAMODEL

Population Size	500
Generation Number	100
Elite Size	1
Tournament Size	3
Crossover Chance	0.9
Mutation Chance (individual)	0.1

3.5. Mainshock Models

The GAModel is completely based on the framework suggested by the CSEP. In it, one forecast is defined as a region in a specfic time interval and is divided in bins. Each bin represents a geographical interval. The whole target area of study is covered by a group of these bins where each bin has an earthquake forecast value. This groups of bin represent the $\mu(x, y)$, the background intensity [18]. In the GAModel, each possible solution is represented as an entire forecast model.

In this context the GAModel is considered as one method to generate space-rate-time forecasts. It also could be described as:

$$\Lambda(t, x, y, M|\Upsilon_t) = \mu(x, y) \tag{6}$$

where you can denote the number of earthquakes forecast in all bins as $\Lambda(t, x, y)$ [15] given that Υ_t is the earthquake observation data up to time t.

The ReducedGAModel, which represents the idea of changing the candidates solution representation (see Section 1), is a method with a similar description of the GAModel. The difference is that, in the ReducedGAModel each possible solution represents only a fraction of the forecast where we expect to find especific risk areas.

The GAModel defines a expected number of earthquakes for every single bin in the target region. That could lead to exhaustive and, sometimes worthless, searches. That is caused by the number of bins in the forecast and also because some in some bins there are no earthquake occurances in the observation data. To minimize this, the ReducedGAModel only define expected number of earthquakes in bins that already had some occurance in the past, giving a direction to where the GA should search.

To make it clear, we use the same example as the one used in [1]. The "Kanto" region, one of the four areas used in both studies, is divided into 2025 bins (a grid of 45x45 squares). Each bin has an area of approximately $25km^2$. The GAModel then calculates an expected number of earthquakes for every bin on a determinated time interval, so the GA searches for good values in 2025 bins.

The ReducedGAModel will first obtain the position of past occurances. Then it will calculate some expected number of earthquakes only for the bins related to those positions. During the development of this method, these positions may vary, including positions that never had earthquake events before. That is important to add some variation to the method. For example, if there are 10 bins with occurances in "Kanto" in the last year, it will make the GA start searching for good values for only those 10 bins, leaving the other 2015 bins empty, representing zero occurances. It is important to highlight that in the worst case, it will make the same amount of searches as the GAModel. The final forecast model will maintain the amount of bins with occurrance, but the number of events for every bin and their location may change.

3.6. Mainshock+Aftershock Models

Hence earthquakes cluster in space and inspired by the space-time epidemic-type aftershock sequence (ETAS), the Emp-GAModel, represents the ideia of associating the GA with empirical laws (see Section 1). It is described as:

$$\Lambda(t, x, y, M|\Upsilon_t) = \mu(x, y)J(M) \tag{7}$$

$$\Lambda(t, x, y|\Upsilon_t) = \mu(x, y) + \sum_{t_i \in t} K(M_i)g(t - t_i)P(x, y) \tag{8}$$

The Emp-GAModel uses $\mu(x, y)$ as defined for the GAModel, so it calculates an expected number of earthquakes for every bin in the target region. P(x,y) calculates the position of the aftershocks with base on the origin of the mainshock. It is a simple space distribuition function, that alocates the aftershocks in one of the following posotions: upper, lower, left or right. It runs for a number of steps, getting futter from the origin at each step or as when there are no more events to be alocated. The Omori law, $g(t)$, which is considered one empirical formula of great success [18] [19] [20], is a power law that relates the earthquake occurance and its magnitude with the decay of aftershocks activity with time. For this approach we used the probabilty density function (pdf) form of the modifed Omori law [18]:

$$g(t) = \frac{(p - 1)}{c(1 + \frac{t}{c})^(- p)} \tag{9}$$

In the paper [19], Utsu says that most p and c values, for various earthquake data sets fall in the range between 0.9 and 1.4, and between 0.003 and 0.3 days, respectively. These values were based on the Davidon-Fletcher-Powell optimization procedure and used in ETAS [19].

Based on paper [21], we set the values of 1.3 for p and 0.003 for c for our the experiments. Following the statement make in this report, we set the time interval t between a mainshock and its aftershocks at one month. The statement says that if the t value is too short, the number of aftershocks is too small, but if it is too big, we may also consider background activity.

For $K(M_i)$, the total amount of triggered events, we count aftershocks within a given area, A, using the following formula, where M_c is the magnitude threshold:

$$K(M_i) = A\ exp([\alpha(M - M_c)]) \tag{10}$$

In the paper [22], it states that α should be equal to the inverse of the magnitude of an event, or $magnitide^{-1}$. To obtain A, the following equation from [21], was used:

$$A = e^{(1.02M - 4)} \tag{11}$$

and lastly, the $J(M)$ is a simulation of the event magnitude by Gutenberg-Richter's Law, using Add SAPP

At last, the Emp-ReducedGAModel is a mix between the ideas in the ReducedGAModel method and the Emp-GAModel, which means that its genome representation is equal to the Emp-GAModel but its candidates have same list of locations format, as in the ReducedGAModel.

4. Tests for evaluating Models

In the paper *Earthquake Likelihood Model Testing* [2], it is proposed some statistical tests that are used in this study, developed by the The Regional Earthquake Likelihood Models (RELM).They were used to compare and evaluate the every forecast models. These tests are based on the log-likelihood score that compares the probability of the model with the observed events.

To evalute the data-consistency of the forecast models we used the N-Test, the Number Test, and the L-Test, or Likelihood Test. These tests fall are significance tests. Therfore, assuming a given forecast model as the null hypothesys, the distribuition of an observable test is simulated. If the observed test statistic falls into the upper or lower tail of this distribuition, the forecast is rejected [16].

To be able to compare the model that passed the N-Test and the L-test, the R-Test, the hypotheses Comparison Test, is used. It calculates the relative performance of a model, by comparing the Log-likelihood values between two forecast models.

4.1. Likelihood Test or L-Test

The L(ikelihood) Test considers that the likelihood value of the model is consistent with the value obtain with the simulations. The value is calculated by the formula, where $\widehat{L}_k$ is the value of the Log-likelihood of the model j, in the *bin* i and $\widetilde{L}$ is the value of the Log-likelihood of the simulation j in the *bin* q:

$$\gamma_q^j = \frac{\left|\left\{\widehat{L}_k^j | \widehat{L}_k^j \leq \widetilde{L}_q^j, \widehat{L}_k^j \in \widehat{L}^j, \widetilde{L}_q^j \in \widetilde{L}^j\right\}\right|}{|\widehat{L}^j|} \qquad (12)$$

The analisys of the results can be splited into 3 categories, as follows:

1) Case 1: γ^j is a low value, or in other words, the Log-likelihood of the model is lower then most of the Log-likelihood of the simulations. In this case, the model is rejected.
2) Case 2: γ^j falls near the half of the values obtained from the simluations and is consistent with the data.
3) Case 3: γ^j is high. This means that the Log-likelihood of the data da is higher that the Log-likelihood of the model and no conclusion can be made what so ever.

It is important to highlight that no model should be reject in case 3, if based only on the L-Test. In this case the consistency can or cannot be real, therefore these model should be tested by the N-Test so that further conclusions can be done.

4.2. Number test or N-Test

The N(umber)-Test also analises the consistency of the model, but it compares the number os observations with the number of events of the simulations. This test is necessary to supply the underpredicting problem, which may pass unnoticed by the L-Test.

This mesure is estimated by the fraction of the total number of observations by the total number of observations of the model.

As the L-test, if the number of events falls near the half of the values of the distruition, then the model is consistent with the observation, nor estimating too much events nor too few of them.

4.3. Hypotheses Comparison Test or R-Test

The Hypotheses Comparison, or the R(atio)-Test, compares two forecast models against themselves. The log-likelihood is calculted for both models and then the difference between them is calculated, named the observed likelihood ratio. This value indicates which one of the model better fits the observations.

The likelihood ratio is calculated for each simulated catalog. If the fraction of simulated likelihood ratios less than the observed likelihood ratio is very small, the model is reject. To make this test impartial, not given an advantage to any model, this procedure is applied symmetrically [16].

4.4. Evaluation

The evaluation process is made as follow: First, the data-consitency is tested by the L-Test and the R-test. If the model passes these tests, meaning that it was not rejected by them, they ares compared with other forecast models, which were also not reject, with the R-Test. The model that best fits the R-Test is then chose as the best model [2].

5. Experiments

To analyze the performance of the forecasts generated by the GAModel, the ReducedGAModel, the Emp-GAModel and finally the Emp-ReducedGAModel, we perfom a simulation. All methods use the folling simulation structure. First, all method evolve using a training data set, then the resulting forecast is analysed against a test data set.

To analise the resulting forecast two evaluation methods were performed. One of the method is the evaluation method proposed by [2] and described in Section 4.4. The other method is the Student's t-test, a statistical hypothesys test, that we use to determine if two models are significantly different from each other.

The data of the JMA catalog was divided into four groups objecting a better understand of the patterns that most influence the earthquakes events and also to be able to determine the qualities of those forecasts. Each group contains only of earthquakes that happened in a specific time interval for a given area of Japan. The experimental data will be described in details subsequently.

5.1. Experimental Data

The data used in these experiments comes from the Japan Meteorological Agency's (JMA) catalog. It is a list of earthquakes events which took place in Japan from 2000 to 2013. Each event is characterized by some typical earhtquake information such as magnitude, latitude, longitude, and depth.

For the experiments we consider events with magnitude above 3.0 which happened in four specific areas of Japan, during the year of ???. Those areas (Kanto, Tohoku, Kansai and East Japan) represent different earthquake attributes and could lead to more information about the power of the forecasts and/or its pitfalls. Kanto, Touhoku and Kansai contain mainly inland earthquakes, which are considered to follow more stable pattern. Figure 1 shows the locations of these four areas. East Japan includes also many off-shore earthquakes. For more information about the four regions please refer to [1].

5.2. Experimental Design

To compare the performance of the forecast models, we execute a simulation experiment on ??? scenarios. Each scenario is defined by a region for a 1-year interval, starting in Jan/01 and ending in Dec/31. To build one scenario, one

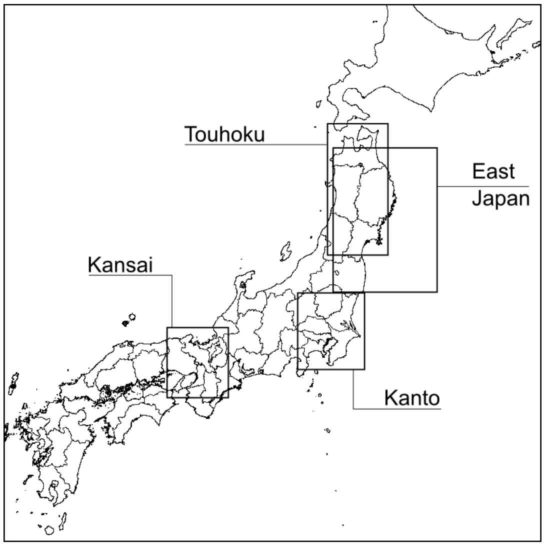

Figure 1. The relative locations of the four areas used in our experiments

region is chosen from the set of regions (Kanto, Tohoku, East Japan and Kansai) for a determinated year. To train the methods, we use 5 years of prior data set. For example, to train the 1-year GAModel forecast model for the year of 2010 in Kanto region, the data used is from the events which occurred in the years of 2006, 2007, 2008 and 2009 in Kanto. This pattern is the same for all methods.

To compare the results of the forecasts models, we used two approaches. The first one is based on the evaluation method proposed by [3] and used in [16]. As described in 4.4, the forecasts were first analysed using the L- and N- test and ?????? was chosen by the R-test as the recommended one.

The second approach is to use the Log-likelihood values obtained by each of the forecast for each scenario. The log likelihood indicates how close the forecast is to the test data, in terms of location and quantity of earthquakes [1].

All methods presented here are stochastic methods. Therefore, to be able to compare and test the statistical significance of the results, we run each forecast model 20 times. This signifies that all results showed are the mean of these 20 executions.

6. Results

7. Conclusions

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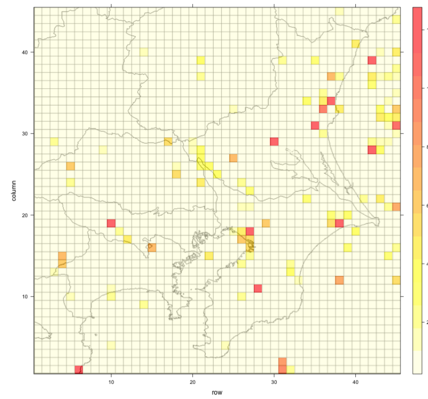

Figure 2. Reduced-Gamodel model for the year of 2009 in Kanto.

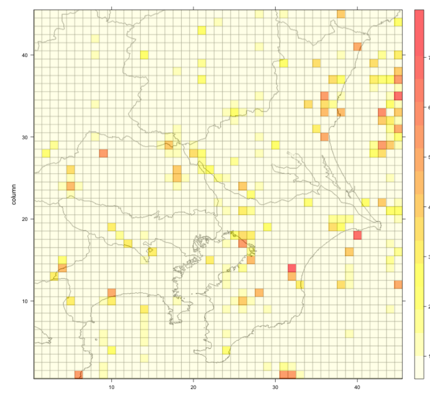

Figure 3. Emp-GAModel model for the year of 2009 in Kanto.

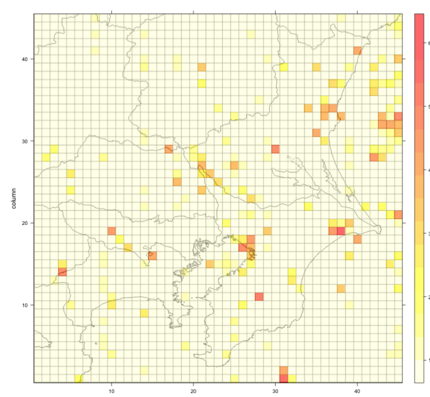

Figure 4. Emp-ReducedGAModel model for the year of 2009 in Kanto.

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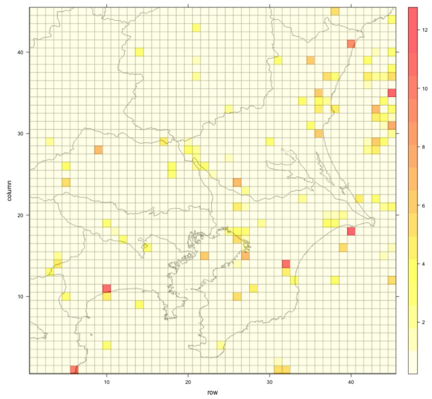

Figure 5. GAModel model for the year of 2009 in Kanto.

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