

Original article

Reprint

Automated map of reproductive losses in the Far North region of Russia

Yaroslav N. Pavlov, Nadezhda V. Savvina

M.K. Ammosov North-Eastern Federal University, Yakutsk, Russia

Received 28 March 2022, Accepted 18 November 2022

Original Text © Pavlov YN, Savvina NV, 2022, published in *Saratov Journal of Medical Scientific Research* 2022; 18 (3): 384–388.
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Abstract: Objective: to compile an automated map of reproductive losses in the Far North regions of Russia. Material and methods: This article includes statistical analysis of the prevalence and structure of reproductive losses according to the worldwide, Russian, and regional statistics. After describing the general structure of a neural network with a radial basis and a model of a radial neuron, we proceeded to characterization of the error backpropagation algorithm. Hence, our study was based on the normal deviation function. Results. The article substantiates the problem of reproductive losses of the Russian population. On the basis of statistical data, the listing of a neural network program for an interactive map of reproductive losses in the Far North regions of the Russian Federation was built. The obtained data made it possible to identify risk zones in the region. Comparison of indicators for 2000 and 2022 helped revealing the dynamics of change and reporting valid information on the overall increase in the risk of reproductive losses in the region by 17%. Conclusion. We proposed to conduct monitoring of reproductive loss indicators in the regions of the Russian Federation on the basis of a neural information map construction. The compiled map is an interactive map with an assessment of reproductive loss dynamics over the years.

Keywords: reproductive losses of the population, interactive map, neural network, Far North regions.

Cite as Pavlov YN, Savvina NV. Automated map of reproductive losses in the far north region of Russia. *Saratov Medical Journal* 2022; 3 (4): e0402.

Correspondence to Yaroslav N. Pavlov. Tel.: +7 (964) 4594681, E-mail: pyn5552007@yandex.ru.

Introduction

The situation with the level and dynamics of reproductive losses is rather ambiguous worldwide. Globally, there are 3.2 million stillbirths and abortions every year, the vast majority of which occur in least developed countries. The prevalence of reproductive losses is typically about 1% of all births in more developed countries of the world and can exceed 3% in the less developed regions [1]. However, each country has its own characteristics of monitoring the dynamics of this indicator. By studying the level of reproductive losses on the basis of statistical data and data from special registers, geoinformation maps are compiled to identify regions and countries with high and critical rates of indicators. This is extremely important, since there is no norm set for reproductive losses and this indicator can only be studied in dynamics and/or in comparison.

Geoinformation technologies constitute an effective tool for the spatial characterization of medical and social issues. Evidence of the relevance and validity of applying the geoinformation system (GIS) to medical and social factors is described in [2–6]. For example, K. Ablyazov, L. Ablyazov, R. Singatulin reported that geospatial data are information that determines the geographical location and properties of natural or artificially created objects, as well as their boundaries on Earth. This is a confirmation that GIS is an up-to-date tool for studying socioeconomic geography [7]. GIS is a centralized database of spatial objects that provides the ability to store, analyze and process any information related

to a particular object, which significantly simplifies the process of use, interpretation and analysis of information [2].

Reproductive loss is a concept that includes both spontaneous and forced (for medical and social reasons) termination of pregnancy, along with stillbirths and death of children in the first year of their life. Abortions are part of the reproductive losses, differentiated by their purpose. To develop a database of reproductive losses in the population, clear criteria are needed for determining medical abortions by indicators and at the request of women, early miscarriages, and early stillbirths. However, the criteria for determining the timing of a miscarriage may differ or contain an error due to an error of 1–7 days in determining the gestational age; it is also difficult to prove the fact of pregnancy termination by appointment.

To construct a GIS map, there are no clear criteria for determining the choice of the database. It is required to include a permissible error range for building an information map. This can be implemented through the neural network design of information systems.

Objective: to compile an automated map of reproductive losses in the Far North regions of Russia.

Material and methods

The materials in our research are statistical data collected in the regions of Russian Federation on population reproductive losses. Age and region were also included in the statistical sample to map the ratio of abortions to live births and stillbirths. We used a statistical analysis of the prevalence

and structure of abortions based on the worldwide, Russian, and regional statistics. For radial network training, an error backpropagation algorithm was used, based on minimizing the objective function of the network error. After describing the general structure of a neural network with a radial basis and a model of a radial neuron, we could proceed to the description of the error backpropagation algorithm. Therefore, our study was based on the normal deviation function.

Results

The distribution of reproductive losses in Russia has significant geographical differences. In the west, there are fewer of them, while the majority of them occur in the central regions and capital area. To track the parameters, taking into account the normal deviation, we built a neural network.

An important element of configuring artificial neural network is the selection of the so-called hyperparameters. The hyperparameters of an artificial neural network can generally be divided into two groups: global and local (related to the nodes).

The global hyperparameters of the overall assessment in Russia include the number of hidden layers, the number of neurons in each layer, the level of training and the moment, and the initialization of neuron weights.

Local hyperparameters for Russian regions include layer type, activation function and other regularization parameters.

The essence operating the radial basis function neural network is as follows. The input vector is introduced in turn to each neuron of the hidden layer, in which support vectors are preliminarily set. Next, the input vector is compared with the support vector. Any metric can be used for comparison, such as Manhattan distance, albeit Euclidean distance is more commonly used. The resulting comparison outcome is processed by the activation radial basis function. The result is then multiplied by the neuronal synapse weight and transmitted to the output layer. The neurons of the output layer sum up received signals and respond, thereby completing the network.

The general structure of the radial basis function neural network is presented in *Figure 1*. The following notation is used: n is the number of elements in the first layer; x_1, x_2, \dots, x_n are the coordinates of the input vector; b is a number of neurons in the second layer; $c_{i1}, c_{i2}, \dots, c_{in}$ are the coordinates of the center of the i -th element; σ_{ij} is the width of the radial function of the i -th element; θ_i is the output signal of the i -th element; w_i is the output coupling weight factor of the i -th element; w_0 is the weight of the bias neuron; y is a network output signal.

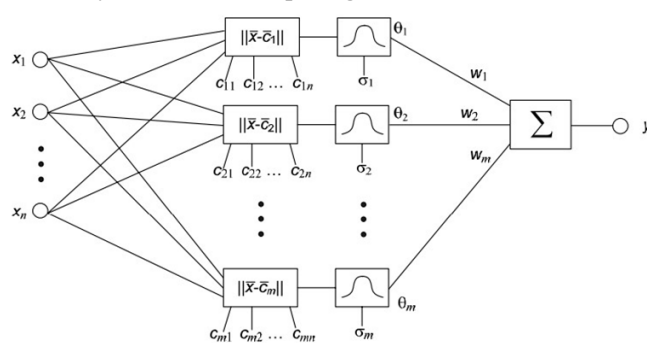


Figure 1. General structure of a radial basis function neural network

The output signal of each element is determined by the Gaussian function. However, depending on the tasks solved by the artificial neural network, the Gaussian function may slightly vary. In the case of solving regression or forecasting problems, the Gaussian function will be defined by the following expression:

$$f(x_1, x_2, \dots, x_m) = g(w_0 + \sum_{i=1}^b w_i \exp(-\sum_{j=1}^m \frac{\sigma_j^2 (x_j - c_{ij})^2}{2\sigma_{ij}^2})) \quad (1)$$

where g is the identification function.

In the case of solving forecasting problems, the number of neurons in the output layer must match the number of classes, and the main difference from regression problems is that each output neuron has its own bias neuron weight value. In other words, an expression (1) becomes:

$$f(x_1, x_2, \dots, x_m) = g(w_{l0} + \sum_{i=1}^b w_{li} \exp(-\sum_{j=1}^m \frac{\sigma_j^2 (x_j - c_{ij})^2}{2\sigma_{ij}^2})) \quad (2)$$

The output signal of the neural network is the weighted sum of the signals of the elements:

$$y = \sum_{i=1}^m w_i \cdot \theta_i \quad (3)$$

Special attention should be paid to the radial neuron. Neurons of a radial type are a natural complement to sigmoid neurons. In a multidimensional space, a sigmoid neuron is represented by a hyperplane that divides this space into two classes in which one of two conditions is satisfied. A radial neuron, on the other hand, is a hypersphere performing a spherical division of space around a central point. In the case of circular symmetry of data, such structure can significantly reduce the number of neurons required for separating different classes.

The main field of using activity diagrams is to visualize the features of implementing methods of the class, whenever it is necessary, to present algorithms for their implementation. Moreover, each state can be the execution of an operation of some class or part of it. The classes of the reproductive loss map are abortions, miscarriages, stillbirths, and live births.

Symbols of neural network branching are used to describe conditional jumps. In particular, parallel connection symbols are used to separate parallel computations or combine control flows.

Of many currently available programming languages, one of the most popular is Java: `eucklidNorm()` and `calculateGauss()` method listings are shown in *Figure 2*.

As soon as the network output is found, the error backpropagation algorithm initiates.

In the backpropagation process, changes in weights, support vector coordinates, and sigma are calculated for each neuron of the network.

The listings of the `gradientCenters()` and `gradientSigmas()` methods accounting for the probable error in estimating reproductive losses are presented in *Figure 3*.

After recalculating the sigma, weights, and support vector coordinates, a new neural network output and root-mean-square error are calculated. If the resulting root-mean-square error is less than the value desired by the user, then the training can be considered completed. Otherwise, training continues until one of two conditions is satisfied:

- the value of the root-mean-square error is less than that desired by the user;
- all training cycles are completed.

Based on the neural network, it was possible to map spatial dynamics of reproductive losses in Russia. The leaders in terms of the number of abortions per 1,000 births were Moscow (405), Moscow Oblast (403), Magadan Oblast (397), and Arkhangelsk Oblast (372) (Figure 4). We also observed a positive trend towards a decrease in the absolute number of artificial terminations of pregnancy provided by substantial reduction in the proportion of unwanted pregnancies from 75.33% (182,548) to 64.80% (101,212), which, in turn, implies a noticeable positive impact of sex education on youth.

```
public double calculateGauss(double[] actual, int index) {
    return Math.exp(-0.5 * (this.euklidNorm(actual,
        arrayofneurons[index].c,arrayofneurons[index].sigma)));
}

public double euklidNorm(double[] actual, double[] ci, double[] sigma) {
    double res = 0;
    for (int i = 0; i < actual.length; i++) {
        res += (Math.pow(actual[i] - ci[i], 2) / Math.pow(sigma[i], 2));
    }
    return res;
}
```

Figure 2. Listings of the euklidNorm() and calculateGauss() methods

```
public double gradientCenters(double[] actual, int indexI, int indexJ) {
    return lastneuron.getWeight(indexI)
        * ((actual[indexJ] - arrayofneurons[indexI].c[indexJ])
            / Math.pow(arrayofneurons[indexI].sigma[indexJ], 2))
        * (calculateGauss(actual, indexI));
}

public double gradientSigmas(double[] actual, int indexI, int indexJ) {
    return lastneuron.getWeight(indexI)
        * ((actual[indexJ] - arrayofneurons[indexI].c[indexJ])
            / Math.pow(arrayofneurons[indexI].sigma[indexJ], 3))
        * (calculateGauss(actual, indexI));
}
```

Figure 3. Listings of the gradientCenters() and gradientSigmas() methods

The data are provided for 2021; however, the study perspective is an interactive map with assessment of the dynamics by years (Figure 4).

As can be seen on the map, the risk of population reproductive losses was high in the Far North regions. To test the compiled map of reproductive losses, we built comparative maps for these regions for years 2006 and 2020 (Figure 5).

Statistical analysis of the maps allows investigating the regional features of demographic losses. Based on Figure 6, we can state that the permissible errors were taken into account, and the dynamics was representative.

Discussion

Our article substantiates the problem of reproductive losses in Russian population. On the basis of statistical data, a listing of a neural network program for an interactive map of reproductive losses in the Far North regions of the Russian Federation was constructed. The obtained data allowed identifying risk zones in the region. Comparison of the values for 2021 vs. 2000 helped revealing the dynamics of change and reporting valid information on the overall increase in the risk of reproductive losses in the region by 17% (Fig. 6).

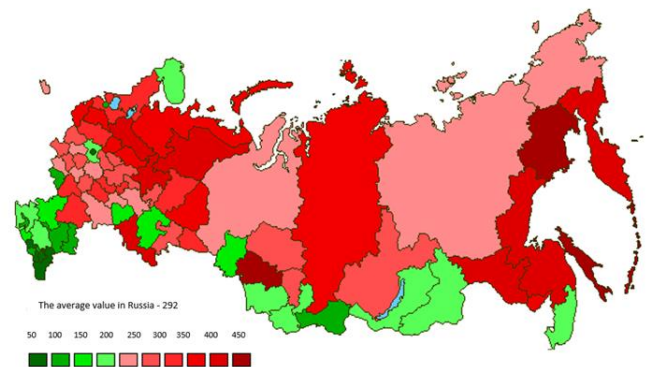


Figure 4. Map of population reproductive losses by the regions of Russia in 2021

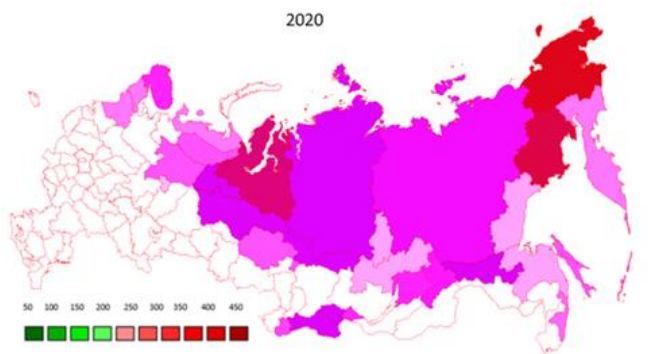


Figure 5. Map of population reproductive losses in 2006 and 2020 in the Far North regions

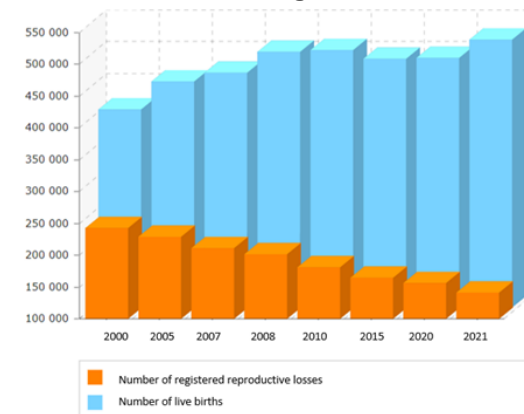


Figure 6. Dynamics of fertility and abortions in 2000–2021

As can be seen, the share of reproductive losses has significantly declined, but the number of reproductive losses in Russia per 1000 births was still among the highest in Europe. In 2000, the share of performed abortions was 58.83% (242,343 over 411,904), while in 2021, it was 27.15% (141,396 over 520,705). Hence, in 2021 vs. 2000, the number of abortions decreased by half (272 vs. 588 per 1,000 births). Such positive dynamics was ensured by an increase in the absolute number of births simultaneously with a reduction in reproductive losses. The dynamics of indicators was inversely proportional, since fewer abortions signified more births.

We compared the obtained results with the studies of previous years and discovered similar dynamics. E.g., in Mapping Edinburgh's Social History [5], we see that the number of reproductive losses decreased over time, which could imply that our data are accurate.

Conclusion

One of the central social problems is birth control and abortion, the solution of which would have a positive impact on educating young people, family planning and improving the demographic situation in the country. Reducing the manifestations of abortions should become a priority for the relevant departments and health care institutions, along with public and religious organizations. Despite significant positive shifts in the dynamics of abortion, their share in the vast majority of Russian regions is one of the highest in Europe.

We propose to perform monitoring of the reproductive loss indicators in Russian regions on the basis of a neural information map construction. Hence, the objective of our study was achieved: to compile an automated map of reproductive losses in the Far North regions of Russia. The research perspective is an interactive map with an assessment of such dynamics over years.

Conflict of interest. The authors of the article declare no conflicts of interest.

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Authors:

Yaroslav N. Pavlov - Post-graduate Student, Department of the Public Health and Healthcare, General Hygiene and Bioethics, M.K. Ammosov North-Eastern Federal University, Yakutsk, Russia;
Nadezhda V. Savvina – DSc, Professor, Head of the Department of Public Health and Healthcare, General Hygiene and Bioethics, M.K. Ammosov North-Eastern Federal University, Yakutsk, Russia.