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PREDICTION AND RISK MANAGEMENT OF SPREADING FOREST PEST INFESTATIONS USING SATELLITE DATA

The article is devoted to predicting the risk of occurrence of large foci of infection in a pine forest with bark beetles, pathogenic fungi, and nematodes. The areas of disease observed on satellite images have a spotted, clustered structure of drying forest. An important statistical characteristic of the infestation structure is the power law of distribution of infestation clusters in size. Large, catastrophic events have a significant probability in processes with power laws of distributions. The given methods of computer identification and analysis of cluster distributions make it possible to form a statistical percolation model of prediction and risk management of forest infestation based on information captured (read out) from space images.

The only effective means of combating the bark beetle is sanitary felling of the forest. The sanitary cuttings area is considered a control parameter in the model. The model uses forest observation on a lattice of satellite image pixels, similar to the lattice of a percolation system. The universality of the theory is explained by the fact that it considers the interaction of elements of infection clusters, which, near the critical state of a forest ecosystem, obey a power-law distribution.

The value of the power-law indicator indicates the formation of large clusters and is used in the model for the risk prediction of infestation development. In the model, risk prediction is understood as a statistical assessment of risk in the future, taking into account changes in the conditions for its manifestation. Changes are determined based on the results of satellite imagery, and the effectiveness of sanitary tree cuttings is considered.

An example of a prediction of the development of forest infestations (drying) using images from the Sentinel-2 satellites is presented. Model identification methods are considered, and a test verification of the model is performed. Using scale-invariant indicators of power-law distributions made it possible to abandon expensive high-precision images and replace them with images of average spatial resolution. The approach to synthesizing a prediction and risk management model from space images discussed in the article is based on the theory of self-organized criticality. The model is quite universal and can be used in space geoinformation technologies to organize effective environmental management.

Keywords: *drying of pine forests; stem pests, remote sensing data, power-law distributions, risk prediction, risk management, percolation model*

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1. INTRODUCTION

The degradation and death of pine forests in vast areas of several European states and other countries worldwide is a serious public concern [15]. This trend, which has emerged in Ukraine over the last decade, has now taken on catastrophic proportions. Data from recent years show that the most common pest species in pine forests in Ukraine, the stem pests *Ips acuminatus* and *Ips sexdentatus*, are rapidly increasing in number. Previously nonaggressive bark beetle *Ips acuminatus* is now considered among the most serious pests of pine forests in Ukraine and other European countries Fig 1. The bark beetle is a carrier of pathogenic fungi and nematodes.

Among serious forest pests in Ukraine, xylophages (stem pests) were taking the dominant position gradually, making up 23 % of the area of all pests in 2018 and increasing the area of its outbreak for 4 years by 7.7 times [5]. Most experts acknowledge that the main factor for the mass infestation of forest pests is the critical state of forest ecosystems in the regions under consideration. The pine bark beetle invades weakened trees, which completely dry up within a short period of a few weeks. The observed mass weakening and desiccation of forests reflect the general critical state of forest ecosystems [8].

The only effective means of bark beetle control are timely identification of infested areas, sanitary felling, and rapid disposal of infested wood [13]. The number of bark beetles caught in pheromone traps is counted to determine the distribution level quickly. In [12], an algorithm for expert prediction of *Ips acuminatus* spread risk depending on environmental factors was proposed.

Figure 1. Forestry territory (June 2019) inhabited by xylophages: *Ips sexdentatus*, *Ips acuminatus*, *Blastophagus minor* (from left to right)

Remote sensing data proved to be an effective tool for detecting and monitoring areas infected with bark beetles, as they provide global, spatially continuous, and periodic data on vegetation status. [11]. In addition, there are now many freely available satellite data sources with worldwide coverage and high temporal resolution (e.g., Landsat and Sentinel programs). These are a cost-effective alternative to costly terrestrial forest field surveys [18]. Remote sensing opens possibilities for detecting and mapping bark beetle infestations based on spectral features of the vegetation. Spectral features are related to various functional and structural characteristics of plants, such as pigment amount, leaf structure, moisture content, nitrogen concentration, leaf surface area index, and other specific indexes. In the current study, the influence of pests is known to be reflected in plants' biophysical and biochemical properties and consequently affects spectral signatures [1]. An analysis of the dynamics of the spread of infestations observed from satellite images reveals the formation of infestation patches. Infestation patches have a coherent (clustered) structure consisting of individual elements (pixels, cells) with at least one side in common. The emergence of such a spatial structure of infestations cannot be described using regular dynamics methods. A statistical model of percolation theory is used to describe the formation of the cluster structure of forest infestations based on satellite images [3].

The percolation model in our research is based on one of the first works by S.R. Broadbent and J. M. Hammerslay on percolation processes [6], which discusses the propagation of liquid (fluid) in inhomogeneous media. A model of spreading an infectious epidemic in a garden on a square grid is considered among the examples. The authors showed that there is a critical value for the probability of infection spreading across the grid cells. Below this value, an epidemic cannot occur, and above a critical value, the spread of large infections (epidemics) occurs with a high probability. Subsequent studies revealed [16, 19] that in a regime close to the critical value, a large percolation cluster of fluid (infection) appears, a power law distribution of infection clusters by size takes place [14], and the percolation cluster has a fractal structure [9]. In our work, we retain the terminology of the first percolation model [6] — “contagion”. Tree infestations are observed from spacecraft as clusters of dead and fresh dead trees of a pine forest populated by xylophages.

If the statistical analysis of the distribution of forest infestation clusters follows a power law [2, 14], then the dynamics of the process may show synergistic (cooperative) properties of environmental factors, which are emergent [4]. The prediction behaviour of systems and processes with such systemic properties cannot be made by studying and subsequently generalizing the effects of individual factors. The occurrence of large outbreaks of pests depends on many factors, including ongoing sanitary measures (tree felling), the initial area of pest outbreaks, air temperature, groundwater levels, soil conditions, tree age, forest stand structure, and others. It is impossible to accurately account for and mathematically describe the impact of even the significant factors influencing the spread of infestations, and a statistical distribution of clusters models their generalizing effect.

A feature of the power law of distribution, also called Zipf law, Pareto distribution, is the slow decreasing probability of large values of a random variable. The power law is one of the indicators of disasters in the natural, technical, and socio-economic spheres [4]. In the case of non-power statistics, the area of large values of a quantity is characterized by a small probability. In systems with a power-law distribution, large events are not rare enough to neglect their probability. The power-law distribution of forest infestation clusters indicates the possible occurrence of large-scale infestation foci. This is because the evolution of the forest ecosystem has accumulated a large amount of a resource (weakened trees), and a favourable combination of environmental factors has occurred that can synergistically affect the deployment of large clusters of infestation foci. This results in the process moving into the high-risk category of large-area tree mortality.

Events that give rise to dangers and risks can be described in statistical language. However, statistics is subject to well-defined deterministic laws. Consequently, risks can be predicted and assessed if process statistics are considered. Risks can be managed by influencing control parameters promptly.

Risk management is the process of identifying, assessing, and taking steps to reduce risk to an acceptable level [17].

The study’s objectives are to substantiate and develop a statistical method and models for risk predicting and managing the drying of a pine forest caused by the colonization of trees by stem pests. This will avoid significant financial losses associated with a decrease in the commodity value of wood damaged by pests. The source data for the statistical method are the remote sensing data over studied areas of the forest.

2. IDENTIFICATION OF A RISK PREDICTION MODEL

The synthesis of a statistical risk model is carried out using forest remote sensing data from spacecraft. The synthesis includes the stages of structural and parametric identification.

The decryption of images. To monitor changes in the composition of the controlled area of the pine forest, optical data from the MSI (Multispectral Instrument) Sentinel-2A, -2B scanner were used. Image interpretation was performed using a pixel-based approach and artificial neural networks [18]. The classification method with learning involved the following steps:

1) creation of a “region of interest” to pre-define 3 classes of objects,

2) histogram analysis and creation of training samples,

3) image classification by artificial neural network method.

This method confidently segments the images into 3 classes: glades and areas of sanitary cuttings, healthy coniferous forests, and areas with completely and partially dried trees. The spatial resolution of the classification result is 10 m/pixel.

Structural identification. By classifying an image of a forest area from a spacecraft, the formation of a cluster structure of infection is established. The size of each cluster in pixels is determined in Fig. 2.

A comparative statistical analysis of the sizes of infection clusters is carried out to identify the model’s structure.

Let $u(x)dx$ be the fraction of clusters with size between x and $x+dx$. Distributions of the form (1) are said to follow a power law:

$$u(x) = Cx^{-\alpha}, \ \alpha > 0. \quad (1)$$

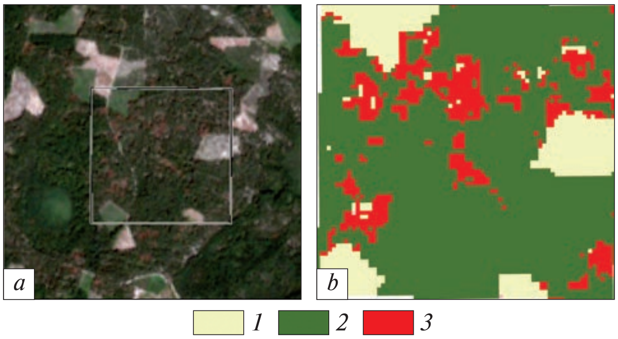

Figure 2. Classification of the image of a test forest area, 2017: *a* — Fragment of the image of a pine forest from the Sentinel-2A spacecraft, the study area is marked with a square in the image for the 2017 year, *b* — Result of image fragment classification: *1* — glades and areas of sanitary cuttings, *2* — healthy forests, *3* — clusters of withered trees

The constant C in Eq. (1) is given by the normalization requirement.

The histogram is a straight line on log-log scales,

$$\ln u(x) = -\alpha \ln x + c \,, \tag{2}$$

where α and c are constants and $c = \ln C$. The constant α is called the exponent of the power law.

In the case of power distributions, huge sample sizes are needed to construct good-quality histograms, which are empirical analogues of probability densities. In most cases, just making a histogram (Fig. 3, *a*) and plotting it on log scales to see if it looks straight is a poor way to proceed. The right-hand end of the distribution is noisy because of sampling errors. In practice, the rank method identifies power distributions, which reduces the requirement for a large volume of statistical data and avoids the early appearance of statistical noise [2, 14]. In order to process the observation data using the rank method, it is necessary to order the sequence of values of variable x in descending order and assign an ordinal number to each element of the sequence, starting from the highest value. Elements with the same value get different numbers in the descending sequence. Each sampled value has a rank equal to the highest element number with that value. The ranks of values are the cumulative frequencies of the distribution, and the maximum value of the cumulative frequency (the total frequency) is equal to the number of items N in the sample. The frequency with which values of a random variable occur, expressed relative to N units, is treated as a statistical probability. Identification of a power rank distribution is done by constructing a probability cumulative function $F(x)$:

$$F(x) = U(X \geq x) = \sum_{x_i \geq x} U(X = x_i) \,, \tag{3}$$

where X — is a random variable and x — is the current value of the variable. The notation below the sum signs in (3) indicates that the summation applies to all values that are greater than or equal to the current value. The probability cumulative function of a power distribution has a maximum value equal to one if $X = x_{\min}$, $F(x_{\min}) = 1$. The function $F(x)$ is defined for both discrete and continuous values. For a continuous value x, the function $F(x)$ is related to the density function $u(x)$ by the integral relation, which takes into account the fact that the power distribution (1) diverges for small values of x,

$$F(x) = \int_x^\infty u(x')dx' = C\int_x^\infty (x')^{-\alpha} dx' = = \frac{C}{\alpha - 1} x^{-(\alpha-1)} = C_1 x^{-(\alpha-1)} \,. \tag{4}$$

Power laws with exponents less than one cannot be normalized and are not usually found in nature [13].

Comparison of relations (1) and (4) shows that the cumulative function $F(x)$ of a power distribution is also a power function with a value of the exponent one less than that a of the function $u(x)$ and is expressed in bi-logarithmic coordinates as a linear relationship:

$$\ln F = \ln C_1 - (\alpha - 1)\ln x \,. \tag{5}$$

In practice, it is possible to construct rank diagrams in natural rather than relative units. Determination of the coefficient of the direct $\alpha - 1$ of the cumulative function in the notation (5) is usually performed using many values of x and $F(x)$ by the least squares method. The method of graphing cumulative functions in bi-logarithmic coordinates is the most obvious method for structurally identifying power-law distributions since the functions' graphs should well approximate straight lines.

Based on the graph of the cumulative function (Fig. 3, *b*), it follows (we can conclude) that the structure of distributions of infection clusters (Fig. 2, *b*) obeys a power law.

Parametric model identification. However, it is known that the least squares method of approximating a power function gives a systematic error in determining α [10, 14]. In [14], the derivation of the maximum likelihood method is recommended to determine the exponent and estimate the statistical error σ. Considering that the value of the power-law index is an important indicator for predicting the occurrence of large infection forest foci, we use these recommendations and the formulas of the maximum likelihood method:

$$\alpha = 1 + n\left[\sum_{i=1}^{n} \ln \frac{x_i}{x_{\min}}\right]^{-1}, \tag{6}$$

$$\sigma = \sqrt{n}\left[\sum_{i=1}^{n} \ln \frac{x_i}{x_{\min}}\right]^{-1} = \frac{\alpha - 1}{\sqrt{n}}, \tag{7}$$

where x_i — the quantities $i = \overline{1,n}$ are the measured values of x and $x_{\min}$ is the minimum value of x, $x_{\min}$ — the minimum value of the quantity x, at which the power law is satisfied, α — the exponent of the power law, σ — an estimate of the expected statistical error.

For the example under consideration (see Fig. 2), exponent values α were calculated using the maximum likelihood method of Eq. (6), statistical error σ — Eq. (7): α = 1.74, σ = 0.09, α = 1.74 ± 0.09, α = 1.74(9). Numbers in parentheses give the error on the trailing figures. The distribution follows a power law, see Eq. (1). The constant C is mostly uninteresting.

3. THE DIVERGENCE OF THE AVERAGE CLUSTER SIZE AS AN INDICATOR OF RISK

Consider the probability density function $u(x)$ of a random continuous variable X with values x, in the notation of Eq. (1). The first-order moment M_1 determines the mean $\langle x \rangle$ and expected value:

$$\begin{aligned} M_1 = \langle x \rangle = \int_{x_{\min}}^{\infty} x u(x) dx = C \int_{x_{\min}}^{\infty} x^{1-\alpha} dx = \\ = \frac{C}{2-\alpha}[x^{2-\alpha}]_{x_{\min}}^{\infty}. \end{aligned} \tag{8}$$

At $\alpha \le 2$, the mean value of the power-law distribution $M_1 \to \infty$, the first-order moment diverges, but at $\alpha > 2$, the mean value is completely determined. From this, we can conclude that the average value of infection clusters tends to be tremendous for the values of the exponent $\alpha \le 2$ calculated by Eqs. (6), (7). Critical value $\alpha_{cr} = 2$. Consequently, significant losses will be associated with catastrophes, which can be predicted from the values of the power exponent calculated at the early stages of forest infection development. It should also be considered that for all-natural systems with values $\alpha \le 2$, the average value of infection clusters is limited by the size of the forest. The distributions are truncated at the tail of large values since the areas of infestation cannot be larger than the area of the entire forest area, see Fig. 3, *b*. This is a finite-size effect. The

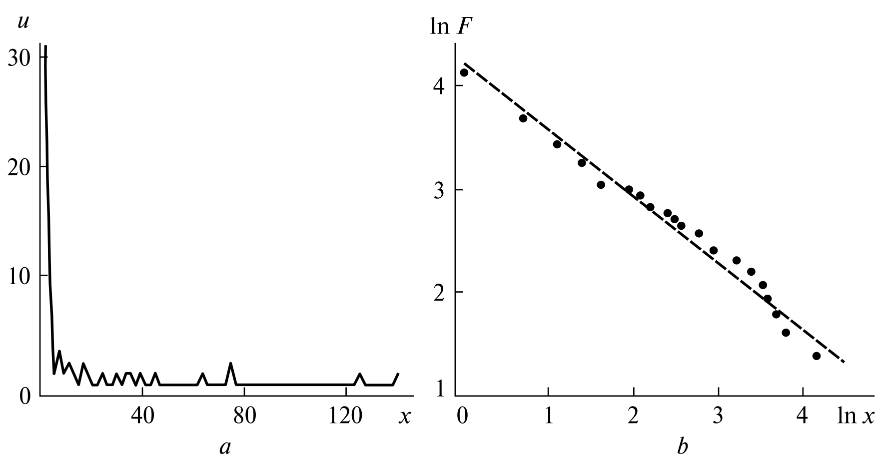

Figure 3. The result of identifying the distribution of infection clusters from a satellite image, see Fig. 2: *a* — histogram, *b* — cumulative functions *F*(*x*) of cluster distribution by size *x*, a straight line on log-log scales

divergence of the average cluster size is determined from the relation (8). At $\alpha \le 2$, further development of the process will generate large values of the sizes of infection clusters. All calculations are performed by a computer program. This program models the process according to the initial data on the areas of infection clusters x received from Remote sensing (Fig. 2). The size of a cluster is determined by its area, which is measured in pixels (1 pixel = 100 m^2). The values of indicator α are calculated by Eq. (6).

Calculating the average size of infection clusters in a percolation forest model. The approximation of the observed distribution by a power distribution is controlled by statistical error σ. When calculating the average value of clusters for $\alpha \le 2$, a specific large, but not infinitely large, number will be obtained. Our data set is not infinite, and the size of the controlled forest area limits the cluster sizes. The size of the infection cluster is determined by decoding the image as the number of pixels of its components. Calculating the average value of clusters for any values of α is performed using the following algorithm.

The type of cluster is characterized by its size. Let there be $i = \overline{1, N}$ types of clusters in the satellite image, then: s_i — size of clusters of type i, n_i — number of clusters of type i. Let p_i be the fraction of infection clusters of type i of size s_i:

$$p_i = \frac{s_i\, n_i}{\sum_{i=1}^{N} s_i\, n_i}, \quad \sum_{i=1}^{N} p_i = 1, \tag{9}$$

then the average size of infection clusters will be determined as a first-order moment

$$< s > = \sum_{i=1}^{N} p_i\, s_i\,. \tag{10}$$

Table 1. **Risk prediction levels**

Risk levels	Comparing Calculated Values $\alpha, \sigma, \alpha_{cr} = 2$
R_1 — low	$2 < \alpha - \sigma$ or the distribution that does not follow a power law, see Eq. (5)
R_2 — medium	$\alpha - \sigma \le 2 < \alpha + \sigma$
R_3 — high	$\alpha + \sigma \le 2$

α — the exponent, critical value $\alpha_{cr} = 2$, σ — error

Risk assessments and recommendations for reducing risk levels. Statistics on foci of forest infestation make it possible to predict three different dynamics of tree death and risk levels: 1) low, 2) medium, and 3) high. The indicator for the prediction assessment is the exponent of the power law α, Eq. (6), taking into account an estimate of the expected statistical error σ, Eq. (7). The average size of infection clusters $<s>$ is calculated using Eqs (9), (10) and characterize the current state of the spread of infection in a forest area. The controlling parameter is the size of the tree felling area. The control parameter can change the prediction estimate. Calculating the current state $<s>$ allows you to evaluate the effectiveness of the control action.

Sanitary measures change the observed structure of infection clusters, requiring a new risk prediction. This concept of risk management based on remote sensing data is implemented by a computer program. The risk prediction levels are carried out according to the relationships given in Table 1.

Risk levels and recommendations: R_1 — planned selective sanitary of tree felling should be carried out, R_2 — new risks may emerge, and risks that were previously addressed may become a problem again, it is recommended to increase the frequency of observations and carry out selective sanitary cuttings of weakened trees, R_3 — tree death is expected over a large area; it is recommended to carry out clear sanitary cuttings of weakened trees.

4. TESTING OF A MODEL FOR PREDICTION AND RISK MANAGEMENT OF DRYING OF THE PINE FOREST

The initial data for predicting the development of foci of infestation of pine forests by the bark beetle were obtained by processing satellite images of a forest area in central Ukraine. The observation was carried out for plantations Pinus sylvestris in the area of the Tobolsk forestry (Volyn region, Ukraine). Trees are 35 years old. The size of the square observation plot is about 53.5 ha, see Fig. 2, *a*.

Table 2 summarizes the main results of predictions and observations of the spread of pine forest dieback in the test area. The drying out of the forest is caused by the colonization of trees by stem pests. Observation of the forest was carried out over 7 calendar years (2015—2021), the dates of filming are presented in the second column of the table. The observation area

$S_2(t_0)$ = 534700 m^2 corresponds to the projections of a 5347-pixel image of the terrain. The data in Table 2 were obtained as a result of space surveys from Sentinel-2A, see Fig. 2, *a*, and further classification of digital images by area: infection, felling, and healthy forest, see Fig. 2, *b*. The calculation of the predictive risk indicator a was performed based on the distributions of infection clusters, Fig. 3, according to model identification methods, see Section 2, and Eqs. (6), (7). The average size of infection clusters $<s>$ was calculated using the method described in Section 3, Eqs. (9), (10). The predicted risk level *R* is determined according to Table 1. The remaining values in Table 2 are calculated according to the equations:

$$\Delta S_1(t_{i+1}) = S_1(t_{i+1}) - S_1(t_i)\,, \tag{11}$$

$$S_3(t_{i+1}) = S_2(t_0) - S_2(t_{i+1})\,, \tag{12}$$

$$\Delta S_3(t_{i+1}) = S_2(t_i) - S_2(t_{i+1})\,, \tag{13}$$

where $i = \overline{0,6}$.

The data given in Table 2 allow you to test the percolation model of risk prediction over observation periods:

• i = 1 the average value of infection clusters is small, $<s(t_1)>$ = 3.97 — the current condition is good, the risk prediction indicator a(t_1) predicts a low level of risk R_1 for the next observation period, sanitary cuttings have not been carried out, $\Delta S_1(t_1) = 0$;

• i = 2 $<s(t_2)>$ = 15.75 — the current condition is satisfactory (the prediction is correct), the risk prediction indicator $\alpha(t_2)$ predicts a high level of risk R_3 for the next observation period, minor sanitary cuttings were carried out $\Delta S_1(t_2)$ = 8, (according to the recommendations, in order for the prediction not to be justified, it was necessary to carry out clear sanitary cuttings);

• i = 3 $<s(t_3)>$ = 57.97 — the current state of infection clusters is characterized by large-scale infection of the forest (the prediction is correct), prediction estimates for the next period $\alpha(t_3)$ and R_3 indicate the death of trees over a large area next year, sanitary cuttings were carried out only of dried trees $\Delta S_1(t_3)$ = = 136 (this does not correspond to the recommendations, see Table 1);

• i = 4 $<s(t_4)>$ = 67.60, the current state — large-scale forest infestation (the prediction is correct), prediction estimates for the next period $\alpha(t_4)$ and R_3 — trees are expected to die over a large area, clear sanitary cutting as have been carried out $\Delta S_1(t_4)$ = 498 (corresponds to the recommendations, see Table 1);

• i = 5 $<s(t_5)>$ = 9.19, the current condition is good due to compliance with the recommendations of last year, the prediction did not come true, the risk prediction indicator $\alpha(t_5)$ predicts a low level of risk R_1 for the next year, sanitary cuttings $\Delta S_1(t_5)$ = 531 were carried out over a large area, which does not correspond to the recommendations of the model and is considered as an unreasonable loss of wood, it is possible that part of the sanitary cuttings from the previous period was transferred to the current period;

Table 2. **Results of prediction and observations of pine forest drying**

i	t_i (observation period)	$<s>$	α	R	ΔS_1	S_1	S_2	S_3	ΔS_3
0	t_0 (initial value)	—	—	—	0	639	4708	639	—
1	t_1 (19.08.2015)	3.97	2.56(20*)	R_1	0	639	4555	153	153
2	t_2 (13.07.2016)	15.75	1.85(11)	R_3	8	647	4327	381	228
3	t_3 (31.07.2017)	57.97	1.74(10)	R_3	136	783	3802	906	525
4	t_4 (10.08.2018)	67.60	1.68(9)	R_3	498	1281	3381	1327	421
5	t_5 (12.08.2019)	9.19	2.22(13)	R_1	531	1812	3205	1503	176
6	t_6 (16.08.2020)	7.67	2.21(12)	R_1	215	2027	2989	1719	216
7	t_7 (03.09.2021)	6.17	2.19(12)	R_1	72	2099	2932	1776	57

*— the distribution does not obey the power law, i — number of the observation period, $<s>$ — average area of dried forest clusters, α — predictive risk indicator, R — predicted risk level, ΔS_1 — forest felling area for the period, S_1 — total area of forest felling at the time of observation, S_2 — total area occupied by forest at the time of observation, S_3 — total area of forest loss at the time of observation, ΔS_3 — forest loss over the period. All areas are given in the areas of projections of image pixels onto the surface, (1 pixel = 100 m^2).

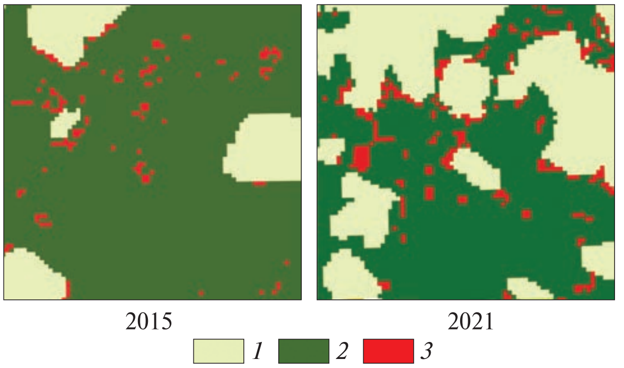

Figure 4. Map of forest losses in the test area of the forestry for the period 2015—2021: *1* — glades and areas of sanitary cuttings, *2* — healthy forests, *3* — clusters of withered trees

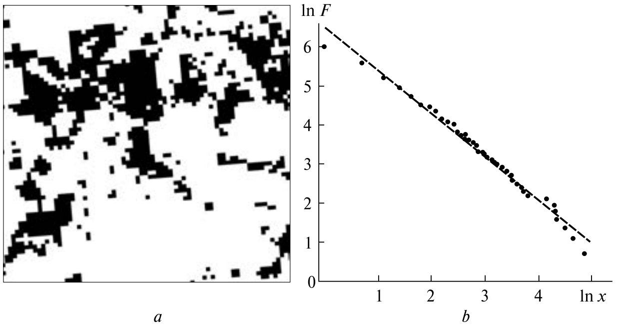

Figure 5. Illustration of verification of the prediction of pine forest infestation distribution: *a* — map of total forest infestation over 6 years (2015—2020), *b* — cumulative functions $F(x)$ of cluster distribution by size x (intensity ranking diagrams). The dots indicate the number of infestation clusters whose size exceeds a given value of x, the linear form of the function in logarithmic coordinates illustrates the implementation of the power distribution law

• $i = 6$ $\langle s(t_6)\rangle = 7.67$ — the current condition is good (the prediction is correct), risk prediction $\alpha(t_6)$ predicts a low level of risk R_1 for the next year, sanitary cuttings have been completed on the square $\Delta S(t_6) = 215$;

• $i = 7$ $\langle s(t_7)\rangle = 6.17$, the current condition is good (the prediction is correct), risk prediction $\alpha(t_7)$ predicts a low level of risk R_1 for the next year, sanitary cuttings have been completed on the square $\Delta S(t_7) = 72$.

Analysis of forest loss in a test area, see Table 2, shows that during the observation period 2015—2021, the percentage of forest loss was $(S_3(t_7)/S_2(t_0))100 = (1776/4708)100 \approx 38$ %.

Figure 2 shows the distribution of sanitary felling and forest drying in 2017. Figure 4 shows the results of interpreting an image from the satellite Sentinel-2A of a test area of the forest in 2015 and 2021.

The map of forest losses in 2021 shows how the areas of forest cutting prevent the formation of a percolation cluster of infection and drying out of trees. The cluster passes through a section of forest from left to right. Figure 5, *a* illustrates the verification of the process of formation of a percolation cluster of infection spread on a site over 6 years. Statistics on the spread of infections obey a power law, see Fig. 5, *b*.

Test model verification over 7 years demonstrated the model's ability to predict the risks of large outbreaks of forest pest infestation. A timely prediction makes the use of clear sanitary cuttings of healthy trees in areas where percolation infection clusters form justified. This will avoid significant financial losses associated with a decrease in the commodity value of wood damaged by pests.

5. CONCLUSION

The percolation model of prediction and risk management of forest infections discussed in the article refers to the formalization of the description and analysis of one of the phenomena of self-organized criticality. The universality of the concept of self-organized criticality is manifested in the general patterns inherent in many phenomena studied in various fields of natural and socio-economic sciences. As first proposed by P. Bak [4], some dynamical systems arrange themselves so that they always sit at the "critical" point of parametric space, no matter what state we start in. One says that such systems self-organize to the critical point or display self-organized criticality.

Such systems develop power-law distributions at particular "critical" points in their parameter space because of the divergence of some characteristic scale [14], such as the mean cluster size in the percolation model.

The value of the power distribution parameter serves as a statistical indicator of a predictive assessment of the risk of the appearance of undesirable large values of the controlled quantity. This indicator is used in the model to decide on the formation of management impacts on the forest ecosystem.

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ПРОГНОЗУВАННЯ ТА КЕРУВАННЯ РИЗИКАМИ ПОШИРЕННЯ
ЗАРАЖЕНЬ ЛІСУ ШКІДНИКАМИ ЗА ДАНИМИ ДЗЗ

Статтю присвячено прогнозуванню ризиків виникнення великих вогнищ зараження соснового лісу жуками-короїдами, патогенними грибами та нематодами. Ділянки зараження, що спостерігаються на космічних знімках, мають плямисту, кластерну структуру всохлого лісу. Важливою статистичною характеристикою структури заражень є степеневий закон розподілу кластерів заражень за розмірами. Наведені методи комп’ютерної ідентифікації та аналізу розподілу кластерів дозволяють сформувати статистичну, перколяційну модель прогнозування та керування ризиками зараження лісу за інформацією, отриманою засобами ДЗЗ. Єдиним ефективним засобом боротьби з короїдом є проведення санітарних рубок лісу. Площі санітарних рубок розглядаються у моделі як керівний параметр.

У моделі використовується спостереження за лісом на решітці пікселів космічного знімку як на решітці перколяційної системи. У процесах зі степеневими законами розподілів значну ймовірність мають великі, катастрофічні події.

Універсальність теорії пояснюється тим, що в ній розглядається взаємодія елементів кластерів зараження, які поблизу критичного стану лісової екосистеми підпорядковуються степеневому розподілу.

Величина показника степеневого розподілу є індикатором виникнення великих кластерів і використовується у моделі для прогнозних оцінок ризику розвитку заражень. У моделі під прогнозуванням ризиків розуміється статистична оцінка ризику у майбутньому з урахуванням змін умов його проявів. Зміни визначаються за результатами зйомки з космосу і враховують ефективність санітарних рубок дерев. Наводиться приклад прогнозування розвитку зараження (усихання) лісу за знімками з космічних апаратів «Sentinel-2». Розглянуто методи ідентифікації моделі та виконано тестову перевірку моделі. Застосування масштабно-інваріантних індикаторів степеневих розподілів дозволило відмовитися від використання дорогих високоточних знімків та замінити їх знімками середньої просторової розрізненості. Розглянутий у статті підхід до синтезу моделі прогнозування та керування ризиками на основі космічних знімків ґрунтується на концепції теорії самоорганізованої критичності. Модель досить універсальна і може використовуватись у космічних геоінформаційних технологіях для організації ефективного природокористування.

Ключові слова: всихання соснових лісів; стовбурові шкідники, дані дистанційного зондування, степеневий розподіл, прогнозування ризиків, керування ризиками, перколяційна модель.