Scenario model to forecast behavior of intrusive plant communities in response to control effects in arid agriculture

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Abstract. The presence of large areas of anthropogenic transformation of plant communities with a potentially negative impact on adjacent territories makes it relevant to develop various methods for automated monitoring and modeling of processes occurring in these ecosystems. Based on the results of previous studies of phytocoenoses, the authors selected four groups of indicators for constructing a scenario model: integral characteristics of intrusive plant communities (IPC), including those obtained by using remote dynamic methods; integral indicators of the negative impact of IPC on the adjacent agro-ecosystem; indicators of the distribution of mobile forms of trace elements in the soil; and indicators of soil microbiota. As the result, a hypothetical formula is obtained that allows, with minimal impact on the biosystem of technogenic IPC, to sufficiently reduce its adverse impact on the adjacent agro-ecosystem. Further refinement and dissemination of the scenario model and its connection to databases on plant communities will automatically change the values of the coefficients in the solving equations, thereby providing the most accurate and reliable forecast of the response of agro-ecosystems to various control actions.

1. Introduction

Plant communities are complex and dynamic ecosystems that determine dynamics and sustainability of other biological systems due to their significant impact on the environment. Plant community systems can be described through diversity of their constituents, intraspecies and interspecies relations as well as consortia between microflora, animals and humans. Dynamics of substances and energy exchange, species diversity and sustainability of these systems have been widely covered by various researchers and mostly depend on soil, climate and other external conditions including human activity [1, 2, 3, 4, 5].

Anthropogenic influence is the factor that impacts ecosystems in areas where intensive human activity leads to changes in natural relief, soil quality and plant communities, enhanced by natural and anthropogenic climate changes. This results in partial deflation of soil cover, degradation of landscape and pollution of adjacent territories and water bodies [6, 7, 8, 9]. This transformation has even bigger intensity and lower predictability in arid zones where restorative power of the nature is smaller and natural factors increasing negative impact on plant communities’ sustainability are additionally expressed [10, 11, 12].

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Hardly eliminable or ineliminable areas where significantly transformed plant communities reach managed agroecosystems are of special interest; these communities can be characterized as intrusive plant communities (IPC) [13, 14]. Applying mechanical and chemical means against these communities is almost impossible due to physical or legal restrictions. As a rule, IPCs have reduced species composition, with 1-2 obvious dominants, and have direct and indirect negative effect on adjacent agroecosystem by disrupting its consortia [15, 16].

The necessity for estimating general conditions of abovementioned plant communities on vast territories of arid phytocenoses, defining tolerable anthropogenic load, applying modern control technologies and tracking their efficiency led to a shift from classical laborious methods of field tests to technologies based on automated analysis and control.

One of efficient solutions involves getting digital images of territories and further computer processing of obtained data using special software. Technologies for obtaining and analyzing remote sense multispectral imagery were successfully used to evaluate forest territories, conditions and biomasses of grazing areas and cultivated territories [17, 18, 19]. The normalized difference vegetation index (NDVI) became the most popular indicator for analyzing remote sense imagery, despite well-known limitations of its information capacity due to atmospheric transparency, observation time and digital imaging resolution [20, 21].

Low-altitude unmanned aerial vehicles (UAV) compensated most downsides of remote sensing although their usage is limited by research area, weather conditions and trespassing restrictions in certain territories. Resolution of images taken by aerial vehicles enables to precisely calculate the biomass and average height of plants as well as forecast dynamic condition of various phytocenoses [22, 23, 24, 25]. Nowadays these results are supplemented by machine learning technologies developing various behavior models of monitored ecosystems [26, 27, 28].

While designing the pilot model forecasting IPCs behavior [29, 30, 31], we faced numerous difficulties related to interpreting multiple data obtained when comparing information about the ecosystem and its environment. We see a possible solution in applying scenario approach that proved its success in forecasting complex systems with mixed, incomplete and partially distorted data that are common for systems highly affected by human factor [32, 33, 34, 35].

The aim of this research was to use scenario analysis for developing the model forecasting properties of semiartificial plant communities that accompany agrobiocenoses of arid zones. This model would enable to find ways to reduce negative agricultural impacts of anthropogenically changed phytocenoses [36, 37, 38].

2. Materials and methods
We have analyzed 28 IPCs located in 9 areas of the Southern Federal District. This enabled us to make necessary generalizations about their impact on adjacent agroecosystems.

While directly studying each IPC in situ, the following key characteristics were specified: surface relief and microrelief, soil type, humus layer depth, anthropogenic effects and adjacent territory specifics. All areas had similar landscape, geomorphological and soil characteristics. In general, relief was leveled out, slightly inclined towards low-lying areas. Soils were light brown, with thin humus layer of about 2-10 cm. Climate and hydrology characteristics were typical for the region.

For determining intrasystemic relations, we singled out key phenotypic traits of participants of studied biocenoses. As part of geobotanical description, we pointed out such aspects as layering, productive covering (PC), total number of species and their phenophas, presence of dominants and subdominants, the level of negative IPC impact on the adjacent agroecosystem – high, moderate or low.

The expert evaluation of IPC influence on the agroecosystem was performed by comparing morphological and phenological indicators of cultivated species and predominant weed plants in the area directly contacting with the IPC (also called “IPC shadow”) and at the distance of at least 50 m from the field. Differences in average height of plants and their number density on these areas, expressed as a percentage, became quantitative indicators of IPC influence on the agroecosystem.
For calculating remote sensing indicators, we used Landsat high-resolution images available at U.S. Geological Survey Earth Resources Observation and Science platform and processed using ArcGISPro software complex. As an integral indicator, we used NDVI reflecting total biomass quantity in studied areas.

Table 1 demonstrates main geobotanical characteristics and results of IPC remote sensing depending on level of IPC negative impact on adjacent agroecosystem.

As field observations clearly demonstrate, IPCs with a high impact on adjacent agroecosystems have higher layering variability, PC and species diversity. These IPCs had relatively high NDVI. Their negative impact on the field is deeply visible – at least at a 40-50 m distance from the IPC border. Technogenic IPCs with low impact on adjacent agroecosystems demonstrated opposite indicators.

We must note that as we expected, the data obtained during the research were insufficient for providing reliable quantitative evaluation of forecasting dynamic IPC impact on adjacent agroecosystems. However, it is possible to forecast the direction of this impact and provide interval evaluation of its intensity. To do this, we applied the research of system dynamics based on functional directed graphs with elements of complex system behavior scenario analysis. To reduce the set of managed elements and control impacts, we formulated limits imposed by agricultural technologies, economy and availability of recommended compound components.

1. Control effects must not affect agricultural phytocenosis (this requirement is determined by the necessity to follow farming technologies).
2. Control effects must be additive. It is possible to increase substance concentration or add a new element but not to exclude it (otherwise either clause 1 is violated or application cost would be higher than the forecasted effect).
3. Control effects must not directly suppress any component of IPC phytocenosis (otherwise it is possible to have a negative impact on species that are planned to be cultivated in the future, i.e. to violate clause 1).
4. The compound formula must not contain more than three components (otherwise cost will increase while reliable forecasting will become impossible).

Table 1. Main geobotanical characteristics of intrusions.

| Indicator                 | Impact on the agro-ecosystem |
|---------------------------|-------------------------------|
|                           | Low (n = 8)                   | Moderate (n = 10) | High (n = 10)    |
| Tiers, m                  | 0.2-0.8                       | 0.2-1.2           | 0.2-1.6          |
| Projective coverage, %    | 20-45                         | 35-70             | 60-80            |
| Total number of species   | 5-8                           | 6-12              | 8-15             |
| The number of dominants   | 0-1                           | 1-2               | 1-2              |
| The number of subdominants| 0-1                           | 0-2               | 1-3              |
| NDVI                      | 0.12-0.24                     | 0.18-0.52         | 0.30-0.62        |

In order to set the decision rules, we singled out in advance the main potentially useful phenotypical traits of participants of studied biocenoses. Basing on previous research, four indicators groups were selected to set the decision rules: IPC integral characteristics, including those obtained via remote dynamic methods (1); integral indicators of negative IPC influence on the adjacent agroecosystem (2); indicators of soil distribution of mobile microelement types (3); and soil microbiota indicators (4).

3. Results
Scenario 3R as a research object is a complex hierarchal structure. Scenario elements can be divided in two groups.
1. General modeling. We needed two sets of possible conditions – for the system \((E \subseteq E^m)\) and its environment \((X \subseteq E^n)\). Here, \(m\) and \(n\) stand for the number of system parameters and its environment parameters respectively that are included in the model, \(E^m, E^n\) are Euclidean spaces of respective dimensions. We define expanded phase space \(Z = X \times Y \subseteq E^{m+n}\). We define the metaset \(M = (M_m; M_E; M_D; M_y_M; M_{mE}; \hat{A});\) where \(M_m = M_y(Y, U, P)\) is the system element corresponding to the studied system, built on \(Y\) substrata, \(U\) set of relations and \(P\) properties, \(M_E = M_E(X)\) is the environment model, \(M_y = M_y(Q)\) is the system behavior model (\(Q\) is the set of possible actions), \(M_{mE}, M_{YE}\) are models measuring conditions of the system and its environment respectively and \(\hat{A}\) is the model (set of rules) of changes in system conditions.

2. Spatial and informational. We need two scales, for the trajectory and for the event (they are also sets, but this time ordered sets). We define them as \(ZT\) and \(RT\) respectively. We also introduce the notion of expertly significant event, which includes a pair \(\mathcal{I} = (z, t), D \in Z\), where \(t\) is time (time interval), depth \(N \in RT\) and horizon \(T = t_n \in ZT\).

3. At the initial stage we accept there is logical dependency and

\[
f_E(x) = f_m(x) = \frac{1}{1 + e^{1(\frac{x}{x_\theta})}} + 1
\]

We call a set of events prior to \(t\) moment a situation:

\[
\mathcal{S}(t) = \{3, (z, t_i, t), 0 \leq t_i \leq t, t_0 = 0\}
\]

Scenario \(\mathcal{H}\) is built according to the rules

\[
\mathcal{H} = \{I(t_i), t_i \in \hat{A}; i = 0, N, t_0 = 0\}
\]

with \(I(t_i) = (S(t_i), M^{Q_H}(t_i))\) as the environment at \(t_i \in ZT \subseteq R\); \(M^{Q_H}\) as the quasiinformational hypothesis (structure of research knowledge or, in other words, accounted uncertainty model).

The beginning of another expertly significant event of scenario \(\mathcal{H}\) at time moment \(t_{i+1}\) is determined by scenario-formulating elements

\[
\mathcal{I}(t_{i+1}) = (S(t_i), M^{Q_H}(t_i), \mathcal{C}(t_i))
\]

with \(\mathcal{C}(t_i)\) as the scenario-forming strategy (continuation means that are available to the operating party).

Three main types of scenarios can be defined and created:
- synergetic, modeling behavioral aspects of the system and describing its development specter in the absence of control effects;
- directly managed, with a chosen complex of control effects;
- attractive, characterizing system behavior according to requirements of a decision-making person, i.e. implementing reverse management objectives.

Providing environmental system scenario research involves performing the following activities:
1. Distinguishing maximal set of significant system parameters (basing on available data on factors affecting dynamics of such systems).
2. Reducing this set for simplifying the model using the expert method that leaves only significant parameters. As a result, we get sets \(E^m\) and \(E^n\).
3. Setting intervals of tolerable (meaningful) values of system parameters – as a result, we get sets \(X, Y, Z\).
4. Forming the ecosystem model graph. Its vertices are elements \(Z\), arcs (set \(U\)) and their weight (in general – functional dependencies, set \(P\)), estimated by the expert method.
5. Defining models of measurement (evaluation) of system and its environment basing on management tasks that have to be sold.
6. Studying synergetic development modes, including defining undesirable events, tolerable impulse impacts for preventing these events, tolerable attractive development scenarios (computer simulation methods), optimal attractive development scenarios (by some optimization methods).

For building the model, during the first stage all discovered dependencies were represented with qualitative characteristics, basing on dividing all mutual (pair) dependencies into 5 groups:
significantly negative (−−−), low negative (−), neutral (undefined = 0), low positive (+) and significantly positive (+++). When necessary, related indicator groups (e.g. PC directly determined onsite and NDVI) were aggregated. All discovered significant dependencies for making decision rules are represented in Table 2 [14, 24].

**Table 2.** Main dependences for constructing a model of IPC system control, summarized according to the data of previous studies.

| Controlling indicator in IPC (substance) | Controlled indicator in IPC (essence) | Connection force |
|----------------------------------------|--------------------------------------|-----------------|
| Soil manganese concentration            | The number of soil bacteria and micromycetes | +++ |
|                                        | The microbiota diversity              | + |
|                                        | Projective coverage                   | +++ |
|                                        | The variety of plant species and phenophases | +++ |
| Soil nickel concentration               | The number of soil bacteria and micromycetes | 0 |
|                                        | The microbiota diversity              | – |
|                                        | Projective coverage                   | 0 |
|                                        | The variety of plant species and phenophases | 0 |
| Soil copper concentration               | The number of soil bacteria and micromycetes | + |
|                                        | The microbiota diversity              | 0 |
|                                        | Projective coverage                   | + |
|                                        | The variety of plant species and phenophases | 0 |
| Soil zinc concentration                 | The number of soil bacteria and micromycetes | +++ |
|                                        | The microbiota diversity              | +++ |
|                                        | Projective coverage                   | +++ |
|                                        | The variety of plant species and phenophases | +++ |

At the next stage, the qualitative data were transformed into coefficients, which values were selected empirically during model testing in stationary mode, to represent the real phytocoenosis dynamics. To do this, we evaluated possible conditions of studied systems – IPCs and agroecosystems, using three relatively independent indicators for each of them (Table 3).

**Table 3.** Indicators of biosystems for model constructing.

| Designation | Value range | Description |
|-------------|-------------|-------------|
| c           | [0, 1]      | Relative projective coverage |
| d           | [0, 1]      | Integral indicator of biodiversity (only for technogenic intrusion) |
| p           | [0, 1]      | Share of dominant culture (only for agro-ecosystem) |
| m           | [0, 1]      | Integral metabolic activity |
Thus, conditions of studied biosystems can be represented as points of unit cubes \( C = \{(c, d, m) \mid c, d, m \in [0, 1]\} \) (for technogenic intrusions) and \( C_a = \{(c, p, m) \mid c, p, m \in [0, 1]\} \) (for agroecosenes). We set the general form of functional dependency between system conditions. \( S(t_0, c_0, p_0, m_0) \) is the agroecosennosis condition at time moment \( t_0 \), while \( S(t_0, c, d, m) \) is the technogenic intrusion condition at time moment \( t_0 \). Let us assume that at moment \( t_0 \) we applied a control effect to the technogenic intrusion and in time period \( \Delta t_1 \) this effect shifted the system to condition \( S(t_0 + \Delta t, c + \Delta c, d + \Delta d, m + \Delta m) \). Then, after time period \( \Delta t_2 \) the agroecosennosis system will change into condition \( S_a(t_0 + \Delta t_0 + \Delta t_1, c + f_c(c), p + f_p(p), m + f_m(m)) \), where \( f_c, f_p, f_m \) are some a priori unknown functional dependencies. We must note that relations of evaluated parameters of these systems are rather hard – this enables to ignore their mutual dependence. These relations are represented as a functional directed graph (Figure 1a).

We have already discussed the formal model of IPC development. However, several rules must be followed:
- minimal impulse at the vertex – 0, maximal – 1;
- the vertex fully loses its impulse in 1 stroke, but this transfer may be delayed (the number on the edge separated from weight by a comma);
- incoming impulse is calculated via multiplying the available (maybe previously available) impulse at the adjacent vortex impulse by the edge weight;
- the sum of weights of all vortex edges must not exceed 1;
- the value of vertex impulse is calculated as the weighted sum of entries transformed though the rule related to the vertex (in our case, a logistic function).

All arguments representing various managing stimuli are dimensionless and determined at segment \([0, 1]\) (Figure 1b).

We evaluated IPC condition using two indicators: PC relative area (c) and IPC biodiversity index (d).

![Figure 1](https://example.com/figure1.png)

**Figure 1.** Dependence of the estimated parameters in agroecosystem on the state of technogenic IPC: a - formalized links in the first stage of modeling; b - formalized links in the second stage of modeling.
To get the opportunity for directly comparing conditions of studied phytocenoses, we introduce integral indicators ($I = \frac{c-1.5(d+m)}{3}$ for the IPC) and ($I_A = \frac{c-1.5(p+m)}{3}$) for the agroecosystem. After the transformation, for IPC: $I = \frac{c}{3} - d$. Index values are within range [-1, 1/3]. Value range asymmetry reflects natural distribution of total factors of agricultural system development (negative stimuli are usually prevailing).

If indicators have a positive value, we consider that conditions are favorable and the system is developing. If indicators are negative, the system is degrading. If after the introduction of the control effect, technogenic intrusion is evaluated by $I'$ indicator, and $I' > I$, we conclude the control effect had a positive influence on the biosystem. If $I' < I$, we consider that the influence is aimed at suppressing system development. If $I'$ and $I$ are equal we assume that the IPC potential remains unchanged. The same principle applies to the agroecosystem.

4. Discussion

The study of scenarios of IPC synergetic development, while assuming the content of metals in the soil constantly remains on an average level ($Mn = Ni = Cu = Zn = 0.5$) and excluding changes in coverage and microbiological soil diversity, demonstrated that the system condition indicator stabilizes at step 21, with $I = 0.013$. The system is stable and is gradually developing.

Now let us analyze several direct management scenarios. After the system has been stabilized, we increase copper compound concentration until it reaches a high level. In this case, the model demonstrates stable indicators of the number of species when $I$ reaches 0.054, partially due to activating soil microbiota metabolism. We should note that average projective coverage area is growing as well. Adding zinc causes rapid changes in IPC eventually leading to phytocenoses degradation with $I$ stabilization at -0.623 (Figure 2.1, 2.2).

The third scenario involves control effects stimulating microbiota subdominants. In his scenario the model acts in the similar way but forecasted degradation is less deep – stabilization happens with $I = -0.357$ (Figure 2.3).

Finally, in the fourth scenario we analyzed the combined impact of simultaneous microbiota subdominants stimulation and addition of zinc. In this case the model shows maximal degradation with $I$ stabilization at $I = -0.71$ (Figure 2.4).

The analysis of the fourth imitation model clearly demonstrates that the most corresponding to biological dynamics and the most efficient (according to forecasts) approach is based on simultaneous adding of mobile microelements to the phytocoenosis soil and stimulation of microbiota subdominants growth and/or metabolic activity.
Figure 2. The IPC dynamics under direct control scenarios – forecast: scenario 1 concluded in addition the copper compounds, scenario 2 provided the zinc compounds administration, at scenario 3 subdominant microbiota was stimulated, and scenario 4 is the combination of 2 and 3 ones. a - projective coverage square (relative, c); b - IPC biodiversity index (d); c - IPC evolvement index I.

We have serious grounds for assuming that application of factors changing condition of soil microelements and microorganisms has serious effects on IPC content and properties. Practical implementation of this approach is possible with the help of biotechnological solutions, in particular, introducing new biotic (bacteria and fungi) or abiotic (chemical substances) elements to the soil.

Data from previous studies combined with our research results indicate that changes in content of soil microelements correlate to a significant extent to microbiota specifics. These specifics can be accompanied with changes in intraspecies and interspecies relations inside the microbiota. This leads to an either negative or positive impact on plant communities. Changes of soil content of
microelements may cause changes in microbe population of communities, prevent growth of non-community plants and lead to formation of new relations between microorganism and plant groups in the agroecosystem.

Fine examples of positive effects are the involvement of microorganisms in zinc assimilation that plays a role in phytocenosis development and increased harvest yield of grain cultures, e.g. Hordeum vulgare L. – the main type of field barley agrobiocenosis.

Presence of micromycetes, in particular pathogenic micromycetes, on the territory of technogenic intrusion is determined by the fact that the soil is a relatively acceptable environment for their growth and development. If the intrusion has a high level of influence on agrobiocenosis, micromycetes largely appear both on intrusion and agrobiocenosis territories.

Primary analysis of phytocenoses revealed that the strongest relations are between aerobic bacteria (predominantly Pseudomonas) and technogenic IPC dominants. Clostridia and bacilli (mostly Bacillus Subtilis and Bacillus sp. MBGLi97) were more often found among dominant basalt microbiota of subdominants and if an Artemisia genus representative was the dominant. No preferences to actinomycetes were found.

Economic value of this modeling is in its opportunity for prompt and low-cost forecasting while calculating potential losses resulting from IPCs as well as in modulation of their processes in order to reduce negative impacts on cultivated species.

5. Conclusion
The result of this research is development and approbation of the scenario model enabling to forecast behavior of plant communities depending on biogenic control effects.

The hypothetical formula, based on this model, that enables to significantly reduce negative impact on adjacent agroecosystem while at the same time having a minimal impact on technogenic IPC must include at least two components.

1. The necessary microelement (or, slightly worse, the natural compound reducing bioavailability of excessive microelement).
2. The stimulator of soil microorganisms growth and metabolic activity (or, slightly worse, microorganisms themselves, because additional substances will be needed for primary adaptation of the introduced microflora).

The modeling data can be used for high-precision management of agrocoenoses development by affecting metal-dependent plant mechanisms for providing required levels of nature usage and reaching optimal economic effects. Further clarification and distribution of the scenario model, its connection to plant community databases would enable to automatically change coefficients of decision equations providing precise and reliable forecasts of agroecosystem response to various control effects.

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