AGRICULTURAL BIOLOGY,
2020, V. 55, № 3, pp. 451-467
(SEL'SKOKHOZYAISTVENNAYA BIOLOGIYA)

ISSN 2412-0324 (English ed. Online)
ISSN 0131-6397 (Russian ed. Print)
ISSN 2313-4836 (Russian ed. Online)

UDC 631.5:519.3

doi: 10.15389/agrobiology.2020.3.451eng
doi: 10.15389/agrobiology.2020.3.451rus

OPERATIVE AND LONG-TERM FORECASTING OF CROP PRODUCTIVITY BASED ON MASS CALCULATIONS OF THE AGROECOSYSTEM SIMULATION MODEL IN GEOINFORMATION ENVIRONMENT

(review)

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The authors declare no conflict of interests
Acknowledgements:
Supported financially from the federal budget under the Agreement on subsidies of December 10, 2019 No. 05.607.21.0302, the project unique identifier RFMEFI60719X0302
Received December 16, 2019

Abstract

In the context of changing socio-economic, natural and climatic conditions, there is a need for effective management tools to adapt agricultural activities. Such tools are farming systems, which are a set of interconnected agrotechnical, reclamation and organizational measures aimed at the efficient use of agrolandscapes, preservation and improvement of soil fertility, and obtaining high crop yields. The efficiency of agricultural production can be improved by using various forecasting methods based on the use of mathematical models. In crop production, statistical and dynamic simulation forecast models have been developed. The latter are more accurate and adaptive and allow you to get an answer to the question about the development of argoecosystems in the conditions of changing climatic conditions and the application of various agricultural measures. The paper provides an overview of methodological approaches for predicting crop productivity based on mass calculations of a simulation model of an agroecosystem in a geoinformation environment that can be used to justify farming systems. The analysis of the state of the problem is carried out, which presents the main current trends in the use of simulation models of agroecosystems in decision support systems for management in agriculture in general and in the support of farming systems in particular. Existing approaches and methods are classified based on spatial coverage into macro-scale, meso-scale, and micro-scale modeling methods. In the general case, these different methods require different methodological approaches are presented in the paper. The relevant basic methods and approaches for creating a universal environment for mass calculations of dynamic models of agroecosystems for different levels of spatial coverage are also presented. The analysis of the very important issue of choosing a set of control (base) points is presented where model calculations will be performed that should belong to real agricultural fields and sufficiently reflect the diversity of soil and climatic conditions of the region under consideration. Also presented are the requirements for a universal modeling environment for carrying out calculations on different models from various suppliers.

Keywords: agroecosystems, simulation modeling, mass calculations, forecasting, geographic information systems, farming systems

The current view on the role of dynamic simulation models of plant production process has changed significantly [1-3]. The scope of application of such models, which has traditionally been limited to scientific research in agroecology, is increasingly expanding towards practical use in decision-making systems [4]. Improved models and theoretical bases of mathematical simulation of processes and phenomena in soil—plant—atmosphere systems allow universal ecophysio-

logical models to be applied to practically unlimited number of crops and soil-climatic conditions [5]. In addition, most modern models of agroecosystems are based on an increasing number of physical and biological determining processes and phenomena [4-7]. Therefore, such models, along with productivity (yield), make it possible to quantitatively evaluate other characteristics of agroecosystems. In model forecasts, there is a transition from single growing seasons to long-term continuous calculations of crop rotations [4]. Also, the idea of a significant variation in the temporal and spatial scale of dynamic models is becoming increasingly popular, in particular, calculations are performed not only for one crop at one geographic point for one growing season, but also for arbitrarily chosen periods of time and territories. In other words, spatial expansion is understood as the simultaneous calculation of a spatially one-dimensional model not only for one selected representative point of the earth's surface with specified soil and terrain properties, but also for a representative set of such points that form a heterogeneous agro-landscape [6, 7]. In contrast to classical one-dimension models of homogeneous sowing, the third-generation dynamic models are applicable to adaptive landscape farming systems [5]. This is due to significant progress in computing technologies, which provide practically unlimited efficiency and speed of calculations of numerical algorithms embedded in the model.

Dynamic models of agroecosystems in decision-making systems. The modeling in decision-making systems requires adequate data input for which all modern tools for on-line monitoring and automated measurements are being introduced in the practice and field experiments, including non-contact methods, remote sensing and portable automatic weather stations [7-11]. Such instrumental methods improve the quality of information for modeling the production process of plants and the reliability of data used for parametric identification and verification of algorithms by assimilating spatially distributed measurement data. Nevertheless, traditional regression models of agroecosystems of varying complexity are currently the most common tool for assessing crop yields on large areas during regional medium- and long-term planning [12-16]. Such models still are basic to regionally assess a potential productivity of the main economic crops for the current growing season. However, in such models the influence of many factors (physical, climatic and technological) may not be fully accounted. Therefore, dynamic simulation models of agroecosystems are a promising forecasting tool that can adequately respond to numerous challenges [17-20]. The methodology of such dynamic model application to regional planning is currently practically absent, and examples of successful medium- and long-term forecasting are few. This is largely due to the fact that adequate spatial-temporal scaling requires adaptation and modification of the internal logic of existing models and the infrastructure of computer experiments [21-23]. Such modification is necessary to provide adequate modeling for long-term crop rotations given the diversity of long-term agro-technological measures [24-27]. The solution can be the use of one model of the production process of agroecosystems for the entire variety of cultivated crops with a common data structure and standard architecture, which will allow application of the model to manage regional farming systems.

The Laboratory for Mathematical Modeling of Agroecosystems, the Research Institute of Agrophysics (St. Petersburg), has been developing and improving the AGROTOOL family of models of production process for 40 years [28, 29]. To date, according to de Wit (30), Agrotool v3.5, a third-level computer model of productivity, has been suggested.

In general, the analysis of the above publications [1-30] allows us to formulate criteria for a model applicable to justify crop rotations in farming systems. The model should regard i) the impact of the predecessor crop, including crop

residues, symbiotic nitrogen fixation by legumes, changes in the agrophysical and agrochemical properties of the soil, etc.; ii) out-of-season abiotic processes ("overwintering"), such as snow cover growth and melt rates, soil freez-ing and warming, etc.; iii) possible explicit indication of doses and timing of agronomic treatments, reactive control modes such as automatic irrigation, sowing date assignment, etc. And finally, the model should be resistant to a lack of factual information. The mentioned AGROTOOL family of models, and, particularly, Agrotool v3.5 fully comply with these criteria.

Also, to expand application of agroecosystem models, stringent criteria should be imposed on the execution environment, i.e. the computer shells [31, 32]. The main requirements are i) a multivariate automated calculation of the model for a large number of alternative options with previously prepared sets of input data and ii) the ability of sequential or simultaneous runs of model calculations. A convenient connection of the execution environment with geoinformation systems (GIS) is also necessary to provide spatial referencing for the soil parameters and a digital model of the relief, and also to visualize modeling results as thematic maps of the indicators [33]. In addition, it should be borne in mind that most forecasting tasks require the procedures for automatic generation of "synthetic" input data (for example, a generator of weather characteristics), which are spatially and temporally coherent [34, 35].

Agronomic dynamic models of productivity are traditionally one-dimensional, or one-point [5]. In other words, each specific version of the model run requires, as input data, information about a specific area of the territory for which the calculation is performed (soil characteristics, relief, weather, etc.). Extending the scope of the model to massive spatial calculations for geographically distributed territories requires the coupling of dynamic agroecosystem models with GIS. Indeed, such a combination provides simultaneous analyses of agroecosystems in time and space [33, 36, 37]. Practical orientation and relevance of such research are obvious. So, prediction of losses of agricultural production due to changes in external conditions, primarily natural, allows practitioners to undertake preventive measures through the choice of appropriate farming system and to maintain a certain level of food security [37, 38]. In risky farming, early warning systems based on remote sensing can help to identify an emerging problem in advance [39, 40]. Often, such systems are based on monitoring weather and agricultural conditions during the growing season and include regionally calibrated crop models for assessing yield uncertainty [41). Yield forecasts can be also made before planting or during the current growing season, and the results can underly managerial decisions to promptly provide alternative options for farming [42].

However, the spatial scalability of a model inevitably leads to the fact that when the scope expands from a point to a territory, the required amount of input information and computing resources increase sharply [43]. Moreover, fundamentally new areas of potential application of relevant technologies in crop and agricultural production have appeared, for example, the use of crop remote sensing data [14, 39, 41, 44, 45], including those for precision farming [10]. To a certain extent, the necessity to obtain all data for mass spatial calculations is avoided in the task of assessing impact of potential climatic changes on productivity and sustainability of an agrolandscape [46, 47]. For a specific calculation option, the required set of input meteorological data (a representative sample of scenarios of weather realizations of the future climate) for an arbitrary spatial grid of control points can be obtained from the IPCC database (Intergovernmental Panel on Climate Change, https://www.ipcc.ch /). However, the methodology has not yet been developed and an adequate toolkit has not been created for the operational model

forecasting of crop productivity for different spatial coverage. Scalability and universalization of the corresponding software and methodological solutions has recently become more and more urgent [48, 49]. Suffice it to say that within the framework of the MACSUR project (Modeling European Agriculture with Climate Change for Food Security, https://www.macsur.eu/), a pan-European information portal on simulation model data support of the European agriculture adaptation to anthropogenic climatic changes, a special working group Scale-It! has been allocated (http://www.scale-it.net/). The group aims to coordinate European research on practical use of crop production models for decision support at various spatial scales [50]. Its scope includes i) organization of ensemble calculations projects, ii) aggregation of specific input data from different geographic locations, iii) substantiation of methods of spatial discretization and spatial interpolation of input data for models with an assessment of the degree of uncertainty of the results obtained, iv) collection of information about personalities, models, approaches, and v) providing operational information on research challenges and achievements on the issue.

The LandCare-DSS environment software (http://www.landcare2020.de/, Leibniz Centre for Agricultural Landscape Research — ZALF, Germany) is one of the most notable applied results of European studies on comprehensive dynamic models of crop yields at regional scale [51]. At present, this software seems to be the only finalized product with an acceptable level of automation [52]. The unique characteristics of LandCare-DSS include its own built-in GIS interface, integration with economic models, and the use of models of different types and spatial detailing within a single architecture, from the YieldStat regression statistical model at a regional level [13] to the dynamic ecophysiological model MONICA for a specific agricultural field [31, 53].

Application of crop yield point models [29] at regional level also requires tools for GIS integration [34, 36, 45, 54]. Suffice it to say that by now almost all most popular models have special shells or extensions for calculations in spatial resolution, for example, the CRAFT platform for the DSSAT family of models [37]. For post-processing (geostatistical and spatial analysis when modeling processes in crops), the Geographic Information System for Agriculture and the Environment (AEGIS; AEGIS/WIN) has been created, which integrates DSSAT models with the geographic mapping tools ArcInfo and ArcView using an object-oriented macro programming language [37]. The GIS-based EPIC model (GEPIC) is another specialized spatial tool that combines the EPIC (Environmental Policy Integrated Climate) biophysical model with GIS to simulate the spatial and temporal dynamics in the soil—plant—atmosphere processes [55]. Back in the 1990s, within the framework of the MARS project coordinated by the Joint Research Center (JRC, European Commission, https://ec.europa.eu/jrc/en), a European crop growth monitoring system (https://ec.europa.eu/jrc/en/research-topic/agricultural-monitoring) and a yield forecasting system based on the BioMA model have been developed [56]. As a result, plant growth and development models became compatible with remote sensing and GIS data [5, 18, 19, 57]. Other solutions in this class include pSIMS, MINK, SIMPLACE and GeoSIM [58-61].

A special task is to use remote sensing data of agricultural lands in dynamic models of agroecosystems [10, 14, 39, 41, 44, 62]. With the advent of remote and even space-based monitoring devices, many soil—plant—atmosphere system characteristics allow direct on-line measurement at almost arbitrarily temporal and spatial resolutions. Moreover, this often does not require any special efforts or expensive measurements, it is enough to have access to partially or completely open and promptly updated databases for processing remote satellite sensing images. The problem, however, is that, despite the development of measuring

instruments, from a mathematical point of view, most agroecological models are still unobservable control systems [63], with only a small part of the state variables available for estimation from observations. Moreover, most of the relevant observations are measurements of indirect quantities, some optical indices, which are undoubtedly related to the essential variables of the model (shoot biomass, soil moisture, chlorophyll content, nitrogen nutrition, etc.), but this relationship is often ambiguous and weakly formalizable [64].

Thus, the analysis of the problem shows that simulation modeling of agroecosystems is a technology based on special studies [54] and currently used in many areas, such as forecasting yield [65], climate change [29, 65, 66)], crop response to various treatments and external conditions [67]. In the very near future, new applications are expected for precision farming and smart agriculture (Smart Agriculture). The world leaders in the area are DSSAT [68] and EPIC [69] (USA), STICS (France) [70], APSIM (Australia) [54], AGROTOOL (Russia) [29], MONICA (Germany) [31], and WOFOST (the Netherlands) [65]. The geography of use of simulation models of agroecosystems is also wide [52, 71]. As in other earth sciences (climatology, hydrology), there is a steady tendency to use not one, but several models (ensemble calculations) for solving specific problems, especially since many of them are freely available [72, 73].

However, it should be noted that simulation models are still little used in applications with long-term forecasts [54, 74], that is, for the development of farming and land use systems, although there are positive examples [75, 76]. The main challenge remains the need to continuously calculate the dynamics of the agroecosystem states for the selected geographic location, taking into account crop changes and non-growing periods. Sometimes for this, a complete description of the crop rotation is directly included in the input data (for example, the MONICA model) [31], an alternative approach is special platforms and shells for the automated transfer of the state of the modeled object from the previous run of the model to the next [76]. Many spatial crop modeling systems have been developed for specific applications and, therefore, have certain requirements and limitations that can significantly complicate their implementation in specific regions. Some of these tools are already outdated (AEGIS) [77], others are very reliable (pSIMS, Mink) [59] and based on scripting languages, so the calculations in these systems must be performed on computational clusters or on high-performance computers. In some models (MARS) [21], it is difficult to solve practical problems of application and maintenance [71], and some solutions are limited in functionality [59]. In this, all researchers point to the need for a convenient and easy-to-use software platform that could become an accessible and adaptable environment for calculating basic models of the crop production to facilitate forecasting the growth and development of plants upon different regional farming systems [39, 54, 78, 79].

Operational and long-term forecasting of crop productivity — a practical overview. A perfect scalable information analytical system for dynamic monitoring and forecasting parameters of an agricultural area should be applicable to develop farming systems at different spatial and temporal detailing levels [80]. For spatial resolution, these tasks are triple. The first group includes macroscale calculations, i.e. assessment of the potential and achievable productivity of the main crops on a national scale for the current conditions (operational time management) and possible climate change (strategic planning in time). The second group is mesoscale calculations, i.e. monitoring of productivity and ecological sustainability of agrolandscapes (operational management) and model-based analysis and optimization of farming systems on a regional scale (strategic management). Finally, the third group includes micro-scale calculations, i.e. analysis (both operational and long-term) of the effectiveness of precision or

coordinate technologies in a farm or in a field. The problems that can be posed and solved using mass calculations of point dynamic models of the agroecosystem at various time and spatial scales, as well as the methods of creating a universal environment for such calculations, are summarized in Table 1 [81].

1. Tasks solved using the simulation model of the agroecosystem at different spatial (SML) and temporal (TML) management levels [81]

TML \ SML	Micro level (a farm, a field)	Meso level (a region, a province, an agricultural holding)	Macro level (country, continent)
Operational monitoring and forecasting	Operational solutions in precision farming Assimilation of remote sensing data into model forecasts	Promptly updating forecast of expected productivity during the current growing season	
Long-term analysis and planning	Farm-level land management projects	Design of regional farming systems strategic impact analysis of new technologies and introduced crops	Assessment of the impact of climate change on agriculture

Mass calculations of the model for a representative set of spatial points should be within a general ideology of batch calculation of all scenarios of the generated computational experiment project, where the scenario's belonging to a specific point is determined by the gradations of "soil" and "terrain" factors [82, 83]. Table 2 shows sources and mechanisms for the on-line data replenishment in calculations of various spatial and temporal granularities [83].

2. Sources and types of input data for modeling productivity of agroecosystems at different spatial detailing (83)

Factor \ SL	Micro level (a farm)	Meso level (a geographic region)	Macro level (country, continent)
Soil	Detailed data on soil sections	Soil maps coupled with cadastral data	Statistic soil maps
Terrain	Coordinates and digital elevation maps	Coordinates	Coordinates
Technology	Operational management: precision farming Strategic planning: automated technology selection	Regionally adapted farming system	Reference regionally adapted farming system
Crop	Crops and varieties of the current crop rotation season	Crops for the analyzed farming system	Basic crops
Weather	Operational management: local automatic weather station Strategic planning: single point weather generator calibrated as per the data of the nearest weather station	Operational management: network of reference weather stations and short-term synoptic forecasts Strategic planning: space-time stochastic weather generator	Operational management: network of reference weather stations and short-term synoptic forecasts Strategic planning: набор эталонных лет-аналогов

N o t e. SL — spatial level.

For a regional scale calculation, it is important to determine a set of control (base) points for model calculations on actual agricultural fields which sufficiently reflect the diversity of soil and climatic conditions of the region. At a regional level, it is reasonable to use not specific, but conditional soil characteristics most typical for the region (e.g., from the Unified State Register of Soil Resources of Russia, http://egrpr.esoil.ru/). Not a specific known option, but an average technology from the recommended farming systems is assigned to the model. There are several variables the values of which determine the initial state of the agroecosystem to which dynamic models are very sensitive during running [84, 85]. Therefore, one should start modeling the current season not from the sowing date, but from a rather long preceding period [76]. In addition, for any geographic location, it is possible to obtain time series of the actually observed weather from the resources of the World Meteorological Organization (WMO, Switzerland) and short-term weather forecasts (https://www.worldweatheronline.com,

https://www.aerisweather.com) for at least 3-5 days [39, 41, 86]. A predictive modeling requires a large number of possible weather scenarios, i.e. so-called analog years [87] or stochastic weather generators [88-90]. Such scenarios have been theoretically developed and successfully integrated in practice into crop computer models. On a regional scale, one can speak of a "good season" and a "bad season" for crop production, which makes it possible to consider a homogeneous region of agricultural production such a geographical area where the interannual variability of productivity significantly exceeds the spatial variability within the region [80].

In Russia, a prototype of an information analytical system has been developed for crop yield model forecasting for different spatial and temporal coverage. The APEX software (Automation of Polivariant EXperiments) [32, 42, 91] was used as the main tool for mass calculations of production process models. Here, multivariate analysis means i) designing and running-up a multidimensional computer case study, ii) performing model runs in batch mode, and iii) applying advanced statistical processing of the results.

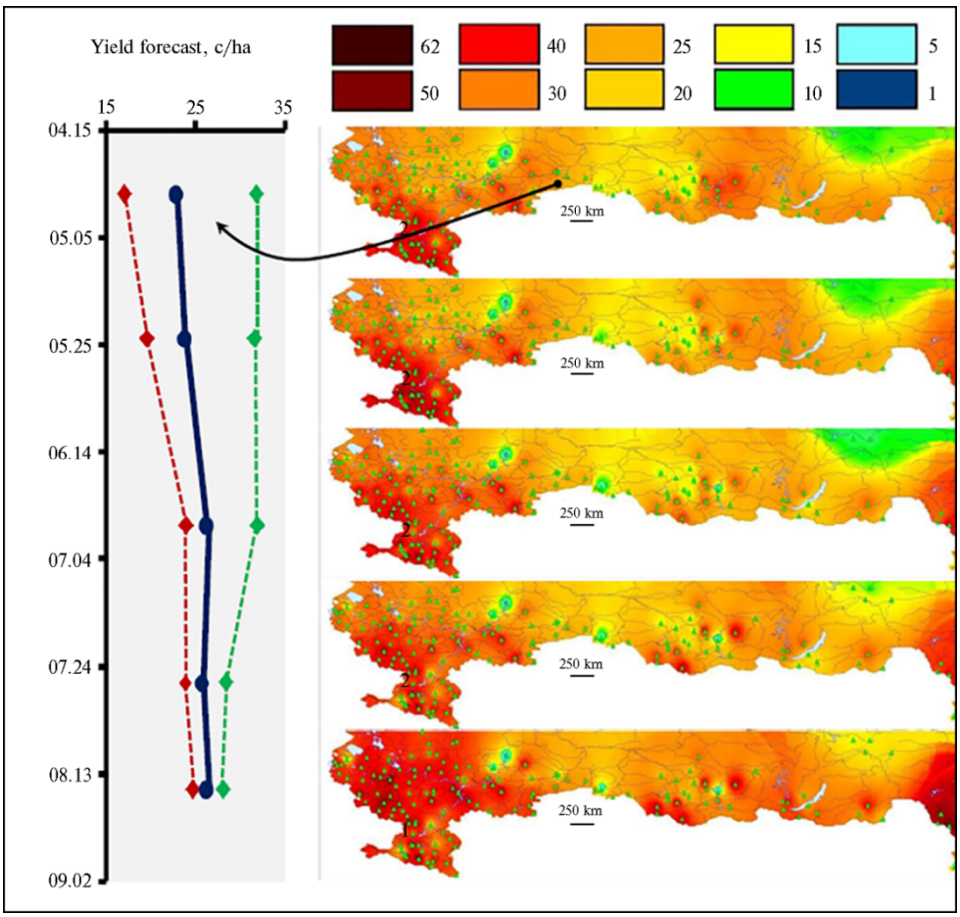

Fig. 1. Dynamically adjusted forecast of the spring wheat yield at different dates in the growing season 2017 for a specific location (left side) **and for Russia** (right side, average values)**.** Green triangles are reference points for calculations [42].

The concept of using dynamic model mass calculations for operational forecasting, proactive management of agroecosystems and satellite sensing data assimilation was theoretically developed in a series of studies [29, 42, 64, 75, 76, 80, 92] and tested, in particular, in Harvest Map tool (https://cropmap.ru/), an electronic map with built-in services for monitoring and forecasting crop production

processes. The dynamic agroecosystem model AGROTOOL allows prediction of the yield of a given crop in a user-selected geographic location [28, 29].

The study of the potential yield of the main crops throughout the territory of the Russian Federation based on a dynamic (promptly refined) forecast of productivity within one current growing season with GIS data visualization is an example of solving the problem of spatial detailing, opposite to those considered above [42]. Selected modeling results are illustrated in Figure 1. The tested approach allows analyzing the evolution of expectations regarding future profitability for the growing season and for all base points together (thematic maps of the predicted average yield on the right side of the figure), as well as the dynamics and interval of the predicted average yield for any specific base point (on the left side of the figure there is a graph for a test point in the Orenburg Province).

The operational and long-term forecasting of spring barley grain yield based on mass calculations of the agroecosystem simulation model in the geoinformation environment was successfully applied in the Republic of Crimea. A digitized electronic map of Crimean soils and scenarios of actual weather conditions from 15 Crimean meteorological stations of the WMO network were used as input data. Calculations for the 2012 and 2014 growing seasons were performed with a grid of 55 selected reference points located in the fields of agricultural enterprises in all regions of the republic. The spatial distribution of the yield of barley and the date of its ripening are presented in Figure 2 (the number of modeling points with the same date of barley ripening is indicated) [80].

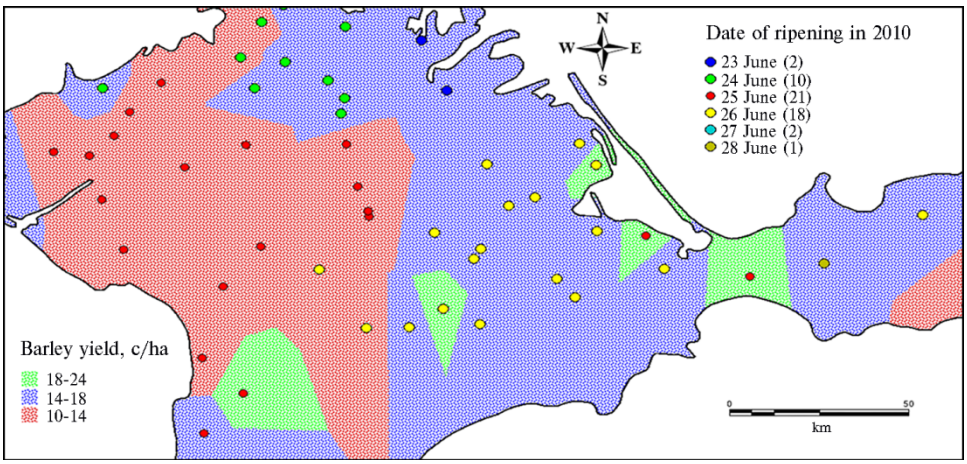

Fig. 2. Spatial distribution of barley yields and ripening dates in the republic of Crimea (the number of modeling points with the same ripening date is indicated in brackets) [80].

We also note a number of studies where the method of multivariate analysis of the dynamics of agroecosystems based on mass calculations of dynamic models of productivity was used for long-term planning [25, 76]. The project of the European Community "Crop growth and soil processes modeling — the use of multi-model ensemble for crop rotations under recent and future climatic conditions" [93-95] is among them. The project aims to apply production process models in assessing possible impact of global climate change on yields and stability of agroecosystems in Eastern Europe, as well as to search for and to analyze the ways to mitigate these negative consequences. As a tool, the researchers chose a popular modern methodology of ensemble calculations instead of one specific model [96]. The fundamental difference between the mentioned project and numerous analogs was the fact that the corresponding ensemble calculations were performed in the context of the selected crop rotation schemes, and the

modification of the traditional practices of crop change was deemed the main investigated mechanism that ensures mitigation of the effects of climate change on agriculture [97-99].

Therefore, modern computing and information technologies create conditions for operational agrotechnological solutions using more accurate and detailed dynamic models. Variable modeling makes it possible to study the effects of various agricultural technologies and assimilate remote sensing data of agricultural areas to select the optimal agrotechnical plan and adjust modeling based on the results of real measurements during the growing season. The number of calculation options and the corresponding model runs are determined by the variation of the following main factors: spatial factor (calculations are carried out in certain locations, each of which is characterized by soil properties and parameters of the simulated crop); meteorological factor (possible weather dynamics for the rest of the growing season is modeled using "options for possible trajectories" consisting of a representative number of synthetic weather scenarios, and for their formation a stochastic weather generator should be used that supports both temporal and spatial correlations); technological factor (for a well-grounded choice of the date, number and parameters of technological operations, it is necessary to analyze the influence of various options in order to choose the best one in the context of the chosen criterion of statistical optimization and to apply a proactive management strategy in crop production); model factor (it is advisable to use not one, but several alternative models of agroecosystems to obtain reliable results).

As a result of simultaneous variation of the above factors with a set of their gradations, the total number of variants of one program-on-model that implement a full factorial computational experiment determines the need to use modern technologies of distributed parallel computing and supercomputer technology. Analysis of the current situation in the design of farming systems allows us to point out the most important role and potential demand of dynamic models of agroecosystems. Decision-makers, in an ideal situation, would like to have a tool that, based on the most diverse sources of information, including remote sensing data, can assess the medium- and long-term consequences of the choice of farming systems. Simulation models of agroecosystems coupled with GIS provide the best environment for solving the optimization of scenarios "what will be if ...". This approach can be a powerful tool in optimizing agricultural land use. Creation of an adequate information analytical system allows farmers and the authorities carrying out planning, monitoring and regulatory functions to make decisions at new level. The tool can be also used as an external intellectual component of state information and analytical resources within the framework of the adopted National Platform for Digital State Management of Agriculture "Digital Agriculture".

Thus, the operational and long-term forecasting of crop productivity based on mass calculations of the simulation model of the agroecosystem in the geoinformation environment plays an important role in the development of farming systems. Empirical regression models based on statistical information are still widely used for regional predictive yield estimates. However, their main drawback is the relatively low accuracy of the results, which makes it impossible to use this approach for operational agrotechnological solutions. The development of computing and information technologies allows us to answer this challenge by applying more accurate and detailed dynamic models of agroecosystems. The choice of optimal agrotechnical plan and adjustment of the modeling process online based on the results of actual measurements during the growing season remain relevant. The main tools are variational modeling, which is used to

analyzed the effects of various modifications of agricultural technologies, and assimilation of remote sensing data, while the best environment is simulation models of agroecosystems coupled with GIS.

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