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Modification Approaches to Improving The Methodological Levels of Innovative Development of Agrocluster Systems

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Abstract: This paper improves methodological approaches to modeling innovation diffusion processes in the innovative development of agrocluster systems. The study substantiates the need to consider the characteristics of agroclusters as multi-actor and multidimensional systems, as well as environmental factors influencing innovation adoption. The capabilities of the existing Bass model in describing innovation diffusion and its limitations in fully capturing the specific features of agrocluster systems are analyzed. An approach is proposed to determine innovation permeability coefficients for political, legal, economic, financial, technological, social, environmental, and geographical layers. The study proposes using a logit model to quantitatively assess these coefficients and modifying the p and q parameters of the Bass model based on their aggregated integral indicator. The modified model also enables the assessment of the maximum diffusion rate, inflection point, and dynamics of innovation adoption. The analysis shows that, under the proposed modification, the regional environment changes the speed and timing of innovation diffusion, while the maximum share of adopters at the point of the highest diffusion rate remains determined by the ratio of the initial Bass model parameters.

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1. Introduction

Agroclusters are integrated systems that connect agriculture with various sectors of production, and their innovative development is important for improving production efficiency and competitiveness. The adoption and implementation of innovations in agrocluster systems are characterized by interactions among multiple stakeholders. Therefore, modeling innovation adoption in agriculture requires consideration of not only economic factors but also social, institutional, and technological factors. Recent studies on innovation adoption models in agriculture have emphasized the multifactorial nature of this process [1].

The Bass model is one of the important approaches for modeling the diffusion of innovations over time. Recent studies have applied the Bass model to describe and forecast the temporal diffusion of innovations, including their initial, growth, and saturation stages [2]. Studies of innovation diffusion have also demonstrated the effectiveness of the Bass model as a mathematical tool for identifying the initial and development stages of various diffusion processes [3]. However, the complex and multi-actor structure of agrocluster systems requires a broader methodological approach than the conventional Bass model. The rate of innovation diffusion may depend not only on

the behavior of innovators and imitators but also on the characteristics of system participants and their interactions. Studies have shown that consumer heterogeneity and network position can affect the rate of innovation diffusion [4].

Research on agricultural innovation diffusion has also highlighted its temporal and spatial characteristics and its relationship with environmental factors [5]. Social influence and institutional mechanisms also play an important role in agricultural innovation diffusion. Studies modeling the adoption of digital technologies in agriculture have considered social influence, adopter behavior, and government policy as interrelated factors in managing innovation diffusion [6]. Recent research has further highlighted the role of multilevel innovation networks and local governance mechanisms in the diffusion of agricultural innovations [7].

From this perspective, representing innovation diffusion in agrocluster systems solely through general diffusion parameters is insufficient. It is necessary to account for the influence of political, legal, economic, financial, technological, social, environmental, and geographical factors. Therefore, this study proposes determining innovation permeability coefficients for these factors and forming an overall integral indicator. The indicator is determined using a logit model and applied to modify the p and q parameters of the Bass model. This approach enables the assessment of innovation diffusion rates and adoption dynamics in agrocluster systems while accounting for environmental factors. Accordingly, the purpose of the study is to improve the methodology for modeling innovation diffusion in agrocluster systems based on this approach.

Literature Review

H. Wang and B. Sun [8] investigated technology diffusion in the new energy industry based on the Bass model and incorporated market and policy environment factors into the model. The study showed that innovators are influenced by expected benefits, while imitators are influenced by actual benefits. L. Liang [9] proposed an optimization-based method for estimating Bass model parameters and evaluated its accuracy using confidence intervals and goodness-of-fit measures. S. Sidorov et al. [10] extended the logistic, Bass, and Gompertz models by accounting for the interaction of multiple unobserved processes. Z. Han et al. [11] developed improved forms of the Bass model for modeling information diffusion, taking into account different user behaviors and the sequential nature of the diffusion process. G. Modanese [12] modeled innovation diffusion in a network environment, considering differences in the probabilities of nodes receiving and transmitting information.

The use of modeling approaches for long-term forecasting [13], artificial intelligence-based modeling of technological processes [14], and risk assessment in energy supply systems [15] demonstrates the importance of modeling methods in forecasting and managing innovation processes. These approaches provide a methodological basis for modeling innovation diffusion in agrocluster systems and accounting for the environmental factors affecting this process.

The above studies demonstrate that the Bass model can be improved in various directions. In particular, incorporating external environmental factors, improving parameter estimation, accounting for additional stages of diffusion, and modeling differences among participants have expanded the applicability of the Bass model. However, modeling innovation diffusion in agrocluster systems by linking it to the political, legal, economic, financial, technological, social, environmental, and geographical environments of a region requires a specific methodological approach. In this regard, determining innovation permeability coefficients and integrating them into the modification of the p and q parameters of the Bass model constitute the main focus of this study.

2. Materials and Method

2.1. Research design

The Bass model was used as the basis for assessing innovation diffusion in agroclusters. The political, legal, economic, financial, technological, social, environmental, and geographical factors of the region were evaluated using a logit model, based on which an integral innovation permeability indicator was developed. This indicator was then used to modify the p and q parameters of the Bass model.

Agroclusters are integrated systems that combine agriculture with various sectors of production, and their innovative development is important for improving efficiency and competitiveness. Innovation adoption and implementation in agroclusters depend on the economic interests, interactions, and social factors of multiple stakeholders, making it necessary to account for network characteristics. Effective innovation implementation also requires assessing management efficiency, system adaptability, and the benefits derived from innovations. Based on these characteristics, the study focuses on representing innovation diffusion and adoption in agroclusters using an approach related to the social influence factors of the Bass model.

The research was carried out in three stages. At the first stage, the classical Bass diffusion model and its optimality characteristics were analyzed. At the second stage, innovation permeability coefficients were defined for the political, legal, economic, financial, technological, social, environmental, and geographical layers of the regional environment, and a logit model was justified for their quantitative assessment. At the third stage, the integral innovation permeability indicator was used to modify the p and q parameters of the Bass model, and the optimality indicators of the modified model were derived.

2.2. The classical Bass diffusion model

The Bass diffusion model was developed by Frank Bass in 1969 to explain how new products or technologies diffuse over time. In the model, the diffusion process depends on two main factors [16]. These factors are innovators (p) and social influence (q). p represents the individuals who are the first to adopt a new product or technology. Their decisions are primarily driven by personal factors and are less influenced by society. Innovators usually constitute a relatively small group. q represents individuals who adopt an innovation after it has been adopted by others. Their adoption decisions are influenced by the behavior of other adopters, that is, by social influence.

Structurally, the Bass model consists of four descriptive parameters and is represented by the following differential equation.

$$\frac{dB(t)}{dt} = p \cdot (1 - B(t)) + q \cdot B(t)(1 - B(t)) \quad (1)$$

Where: $B(t)$ – the proportion of adopters who have adopted the innovation over time t ; p – the probability of adopting the new technology due to the influence of innovators; q – the probability of adopting the innovation due to social influence (the influence of society and social interactions), or the proportion of consumers who adopt the innovation under the influence of others (imitators), representing the imitation coefficient; t – time.

This equation represents the innovation and its cumulative impact on the future potential market. The rate of gradual changes in sales, derived from periodic sales or previous trends, is proportional to the combined effects of innovation and imitation on the market over time. Bass expressed the analytical continuous-time solution of his equation as follows:

$$B(t) = \frac{1 - e^{-(p+q) \cdot t}}{1 + \frac{q}{p} e^{-(p+q) \cdot t}} \quad (2)$$

The p and q parameters of the Bass model characterize the diffusion process and, through their interrelationship, define specific criteria [16]. In particular:

if $p > q$, the innovation is adopted independently and diffuses rapidly;

if $p < q$, consumers are more influenced by social factors when adopting the innovation; diffusion starts slowly but accelerates later;

if $p \approx q$, the innovation diffuses naturally in a balanced manner.

In addition, the critical value of time and the corresponding levels of optimality were subsequently determined (Table 1).

Table 1. Criteria for the Bass Model Time Parameter Based on the Optimality Measure

Symbol	Classification of Specific Criterion Indicators	Formula
t^*	Maximum diffusion rate point. At this point, the number of innovation adopters reaches its highest level.	$t^* = \frac{\ln(q/p)}{p+q}$
t^{**}	Turning point times	$t^{**} = \frac{\ln\left(\frac{q}{p}\right) - \ln(2 \pm \sqrt{3})}{p+q}$
$f(t^*)$	Maximum diffusion rate	$f(t^*) = \frac{(p+q)^2}{4q}$
$B(t^*)$	Maximum proportion of innovation adopters	$B(t^*) = \frac{1}{1+p/q}$

These formulas are used to analyze the dynamic characteristics of the Bass model. Although the Bass model describes the diffusion of innovative products and technologies, it does not fully account for the complex interactions within production and cluster systems. Agroclusters are multi-actor systems that integrate farmers, processors, logistics networks, innovation centers, government institutions, and investors. Therefore, it is necessary to improve the Bass model by incorporating the multidirectional diffusion of innovations, the innovation environment, and the influence of external conditions.

2.3. Existing modifications of the Bass model

In [17], the influence of the p and q parameter values of the Bass model on diffusion patterns is examined, along with the corresponding p - q Euclidean space maps. The scientific approach and the essence of the proposed Bass model improvement are related to the diffusion of innovations across differentiated regions, and a solution is developed for the special case of $p+q=0$. For this case, the Bass model does not provide a solution; that is, its parameters are limited in addressing such cases according to the definition of the object, and this relationship has no meaningful logical interpretation. In [18], the Bass model was modified to provide a more accurate assessment of processes using empirical parameters and shorter time intervals. In [19], the possibility of adapting the Bass model to complex economic processes was investigated. In particular, two improved Bass models were successfully applied to forecast the economic development parameters of the film industry. In the first case, the probabilistic parameters of the Bass model equation were introduced as complex variables, whereas in the second case, the levels of the p and q parameters were applied.

3. Results

3.1. Innovation permeability coefficients of the regional environment

Based on our analysis of the improvement methods successfully applied in previous studies, we consider enhancing the accuracy of modeling innovation diffusion processes in agrocluster systems and extending their economic interpretation by integrating innovation permeability coefficients into the Bass model.

In our approach, the innovation permeability coefficients that define the criteria for increasing the innovation potential of an agrocluster system are as follows. In particular:

- k_1 - innovation permeability coefficient of the political layer;
- k_2 - innovation permeability coefficient of the legal layer;
- k_3 - innovation permeability coefficient of the economic layer;
- k_4 - innovation permeability coefficient of the financial layer;

k_5 - innovation permeability coefficient of the technological layer;
 k_6 - innovation permeability coefficient of the social layer;
 k_7 - innovation permeability coefficient of the environmental layer;
 k_8 - innovation permeability coefficient of the geographical layer.

Here, the innovation permeability coefficient of the political layer (k_1) is defined as an integral indicator calculated based on the following indicators: the effectiveness of government policy in creating innovation infrastructure in the agro-industrial system (k_{DSS1}); the effectiveness of government policy in developing intersectoral integration and cooperation in the agro-industrial system (k_{DSS2}); the effectiveness of government policy in export strategy and financing mechanisms in the agro-industrial system (k_{DSS3}), and the effectiveness of government policy in human capital development and training in the agro-industrial system (k_{DSS4}). It is determined as follows:

$$k_1 = (\prod_j k_{DSS(j)})^{0,25} \quad (3)$$

For all other layers, the methodology for calculating the permeability coefficients is not expressed in terms of composite indices. This is because the quantitative determination of environmental parameters considered within these layers is based on relatively complex approaches. Study [20] shows that the complex structure of socio-economic objects requires the identification of their constituent elements and the determination of their priorities. Study [21] highlights the challenges of quantitatively assessing qualitative indicators and constructing multidimensional data in the study of natural and socio-economic systems. These approaches justify the need to account for environmental factors when econometrically modeling complex objects.

However, in our view, there are cases in which the outcome of the analysis requires the development of an entirely new indicator, or where modeling aspects of system elements that lack direct quantitative characteristics should be based on previously established modeling approaches or models. The main requirement is that such approaches should be logically and methodologically consistent and should not lead to contradictions.

Based on the above considerations, in the innovative formation and development of agrocluster systems, it is appropriate to determine the innovation permeability coefficients of the regional environment including social, economic, legal, and other dimensions—through indicators reflecting socio-economic events and the system's response to changes and innovations in the external environment. In our approach, logit (logistic) modeling provides an opportunity to quantitatively express the innovation permeability coefficients of these environmental dimensions. This can be justified by the following considerations.

First, the logit model accounts for the individual effects of environmental factors and measures the influence of each factor on the probability of innovation adoption. Second, this model reflects a feature analogous to that of the Bass model, but at a different level of analysis. While the Bass model describes the general characteristics of innovation diffusion at the macro level, the corresponding feature is retained in the logit model at the micro level, where the effect of each environmental factor on the probability of innovation adoption can be assessed explicitly. Environmental factors need not represent macro-level characteristics; rather, they may be indicators reflecting any significant aspect of the environment.

In statistics, a logistic model (or logit model) is a statistical model that models the log-odds of an event as a linear combination of one or more independent variables [22].

Based on the characteristics of the object under consideration, the general form of the logit model can be expressed as follows:

$$P(Y = 1|X) = \frac{\exp(-\beta_0 - (\sum_{i=1}^m \beta_i \cdot X_i))}{1 + \exp(-\beta_0 - (\sum_{i=1}^m \beta_i \cdot X_i))} \quad (4)$$

In our case, the variables of the logit model are classified as follows.

Here, P is the probability of the degree of propensity of the existing environment in the agrocluster system toward innovative development; Y is the dependent variable ($Y = 1$ – prone to innovative development, $Y = 0$ – not prone); X_i – represents the independent variables, i.e., a set of factors characterizing the legal environment. The classification of the model parameters is presented in the following table (Table 2).

Table 2. Classification and Economic Interpretation of the Logit Model Parameters

Symbol	Parameter Classification	Economic Interpretation
β_0	Model intercept	The existing level of innovation adoption in the system when other factors are zero
β_i	Effect of each factor on innovation	The intensity of environmental factors that have a positive or negative effect on the innovation process
e^{β_i}	Odds ratio (relative odds)	Represents how many times the odds of innovation adoption change when the X_i variable increases by one unit

Thus, the subsequent innovation permeability coefficients that define the criteria for increasing the innovation potential of the agrocluster system are determined based on the high-approximation variance level obtained from the logit model, as follows:

$$k_j \leftarrow P_j, (j = 2, \dots, 8) \quad (5)$$

3.2. Integral indicator of innovation permeability

Based on the innovation permeability coefficients that define the criteria for increasing the innovation potential of the agrocluster system in the region, we calculate the overall integral indicator (IK) as follows:

$$IK = \left(\prod_{j=1}^K k_j \right)^{1/K}, (K \in N) \quad (6)$$

Here, K – represents the number of major influencing layers in the innovative development of agroclusters in the region; in our case, $K = 8$.

The algorithm for determining the innovation permeability capacity of the region in forming innovative agroclusters is presented in Figure 1.

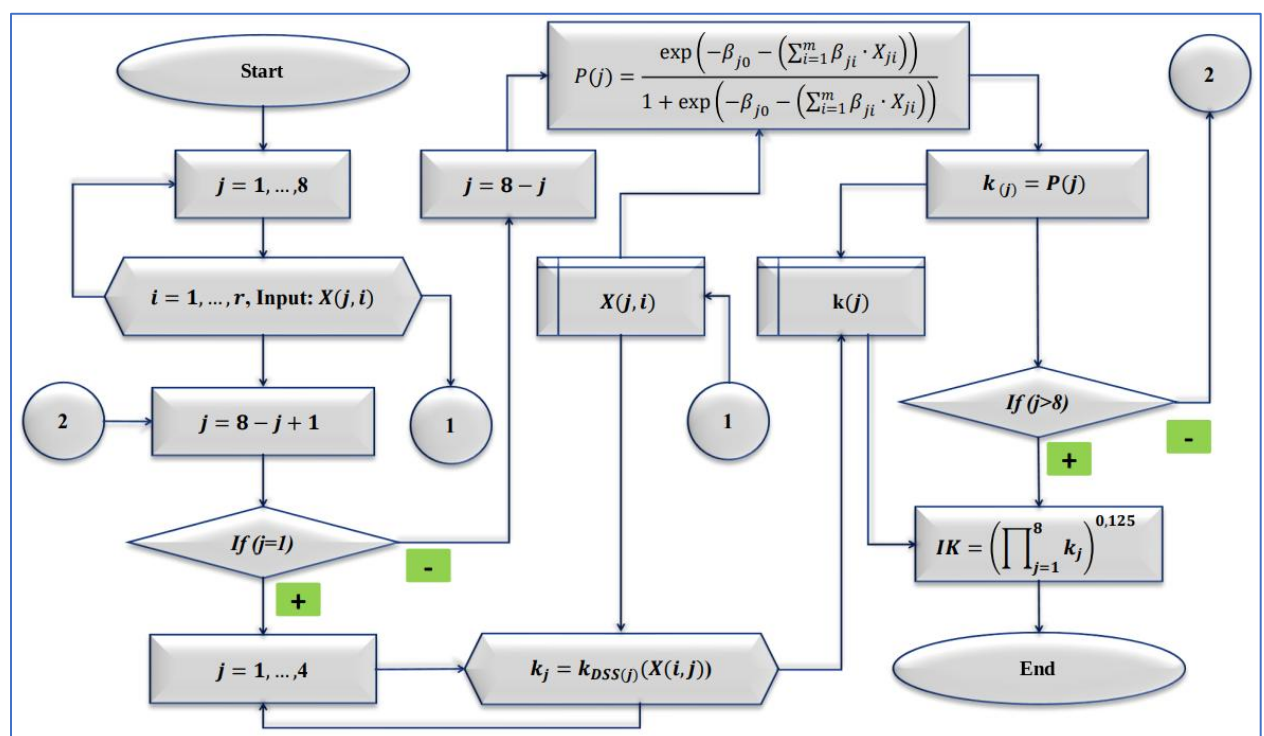


Figure 1. Algorithm for determining the regional innovation permeability coefficient in the formation of innovative agroclusters

3.3. Modified Bass model for agrocluster systems

Next, we propose modifying the p and q parameters of the Bass model using the innovation permeability coefficients. In this regard, we introduce the concept of the initial parameters of the Bass model. In fact, by its nature, the Bass model does not account for environmental factors in the innovation diffusion process. Therefore, the initial parameters are the coefficients determined beforehand without considering these environmental factors.

For clarity, we denote these parameters as p_0 and q_0 . It should be emphasized once again that these parameters directly belong to the original Bass model. Specifically p_0 is the basic innovation adoption coefficient (the proportion of innovators), indicating the extent to which the agrocluster system independently adopts an innovation when environmental factors are not considered. Similarly, q_0 is the basic imitation adoption coefficient (the proportion of imitators), indicating the extent to which the agrocluster system can increase its innovation index under the influence of its independent decision-making capacity when environmental factors are not considered.

The improved model proposed in this study reformulates the Bass parameters by incorporating environmental factors. In this approach, the overall integral indicator calculated from the innovation permeability coefficients, which define the criteria for increasing the innovation potential of the agrocluster system in the region, is used as the modification parameter.

Accordingly, the modified parameters p and q can be expressed as follows:

$$\tilde{p} = p_0 \cdot IK, \quad \tilde{q} = q_0 \cdot IK \quad (7)$$

Three cases can be distinguished in relation (7) depending on the quantitative value of the integral coefficient (IK):

if $IK > 1$, the environmental factors have a positive effect on innovation diffusion, and the values of $\tilde{p}$ and $\tilde{q}$ increase;

if $IK < 1$, the environmental factors constrain innovation diffusion, and the values of $\tilde{p}$ and $\tilde{q}$ decrease;

if $IK = 1$, the initial Bass model parameters, without considering environmental factors, remain quantitatively unchanged; that is, the unmodified Bass model is retained.

In an agrocluster system, quantitatively determining the p_0 and q_0 parameters in equation (7) naturally results in a complex probabilistic formulation. This is because assessing the innovation activity of agroclusters and their members requires consideration of a large number of indicators. In this case, we consider it appropriate to use a composite index that reflects the overall scale and characteristics of these indicators. Therefore, we use the Innovation Development Index (IRI) of the Republic of Uzbekistan. A linear relationship between the p_0 and q_0 parameters and the IRI is unlikely, as their dynamic changes may exhibit substantial disproportionality. Therefore, considering that the p_0 and q_0 parameters take values between 0 and 1, we examine this relationship using a Beta regression (logistic function), as follows:

$$p_0 = \frac{\exp(a_0 + a_1 \cdot IRI)}{1 + \exp(a_0 + a_1 \cdot IRI)}, \quad q_0 = \frac{\exp(b_0 + b_1 \cdot IRI)}{1 + \exp(b_0 + b_1 \cdot IRI)} \quad (8)$$

Here, a_0, a_1, b_0, b_1 – model parameters.

This methodological improvement enables more accurate modeling of which factors accelerate or slow down innovation diffusion in the agrocluster system. As a result of this modification, the optimality indicators of the Bass model take the following formal form. In particular:

Maximum diffusion rate point: (t_M^*)

$$t_M^* = \frac{\ln(q_0/p_0)}{(p_0 + q_0) \cdot IK} \quad (9)$$

This point represents the time at which innovation diffuses at the highest rate, or when the rate of change in the number of innovation adopters reaches its maximum. This time identifies the stage at which cluster members adopt the innovation most actively. In

particular, it represents the optimal period for implementing programs that support the adoption of new technologies.

Turning point time: (t_M^{**})

$$t_M^{**} = \frac{1}{(p_0 + q_0) \cdot IK} \quad (10)$$

This point represents the time when innovation diffusion approaches the turning point. It indicates changes in the intensity of the diffusion process. It reflects the period when the rate of innovation diffusion begins to slow down, typically after the level of widespread innovation adoption has increased.

Maximum diffusion rate: $(f_M(t_M^*))$

$$f_M(t_M^*) = \frac{(p_0 + q_0)^2 IK}{4q_0} \quad (11)$$

This modified parameter represents the value at the moment when the rate of innovation diffusion reaches its maximum. From an economic perspective, it generally reflects the efficiency of investment.

The modified equation for the rate of innovation adoption in the agrocluster system represents the proportion of innovation diffusion at a given point in time and can be expressed as follows:

$$f_M(t) = \frac{dB_M(t)}{dt} = [p_0 \cdot (1 - B_M(t)) + q_0 \cdot B_M(t)(1 - B_M(t))] \cdot IK \quad (12)$$

Here, $B_M(t)$ -the proportion of innovation diffusion in the agrocluster system, the modification of which follows from the following relationship:

$$B_M(t) = \frac{1 - e^{-(p_0 + q_0) \cdot IK \cdot t}}{1 + \frac{q_0}{p_0} e^{-(p_0 + q_0) \cdot IK \cdot t}} \quad (13)$$

In equation (12), a low value of $f_M(t)$ indicates a high level of anti-innovation density in the overall environment (social, economic, legal, and other factors) for innovation adoption in the agrocluster system. This implies the existence of substantial internal potential resistance to achieving investment and labor efficiency in the regional agrocluster system.

4. Discussion

The proposed approach extends the Bass model in a direction that differs from the modifications reviewed above. Previous studies incorporated market and policy environment factors into technology diffusion [8], improved parameter estimation [9], accounted for multiple interacting processes, behavioral differences, and network structures [10]–[12], and adapted the model to specific empirical settings by modifying its parameters [17]–[19]. In contrast, the present study links the p and q parameters to a multilayer characterization of the regional environment through innovation permeability coefficients. This makes it possible to represent the political, legal, economic, financial, technological, social, environmental, and geographical conditions of agrocluster systems within a single diffusion framework.

An important property of the modification in (7) follows from the fact that both parameters are multiplied by the same integral indicator IK . Since the ratio of the modified parameters remains equal to q_0/p_0 , the maximum proportion of innovation adopters at the point of the highest diffusion rate, $B(t^*) = 1/(1 + p/q)$ (Table 1), is not affected by environmental factors. At the same time, according to (9)–(11), the time of the maximum diffusion rate and the turning point time are inversely proportional to IK , whereas the maximum diffusion rate is directly proportional to IK . Thus, in the proposed model, the regional environment primarily determines the speed and timing of innovation diffusion in agrocluster systems rather than the shape of the diffusion curve: a favorable environment ($IK > 1$) accelerates diffusion and shifts the peak of adoption to an earlier period, whereas an unfavorable environment ($IK < 1$) slows diffusion and delays the peak.

From a practical perspective, the integral indicator and its layer-specific components make it possible to identify which environmental layers constrain innovation diffusion in

a particular region. Because IK is calculated as a geometric mean (6), a low value of any single permeability coefficient substantially reduces the integral indicator. Consequently, improving the weakest layer of the regional environment can produce a larger effect on diffusion dynamics than further strengthening layers that are already favorable. This property makes the approach useful for prioritizing regional measures that support the formation and innovative development of agroclusters.

At the same time, the proposed approach has several limitations. First, the model has been developed at the methodological level and has not yet been estimated using empirical agrocluster data; therefore, the values of the permeability coefficients, the integral indicator, and the modified diffusion parameters are not quantified in this study. Second, the estimation of the logit models requires sufficiently detailed data on the environmental factors of each layer, which may be limited at the regional level. Third, the use of a single integral indicator to modify both p and q assumes that environmental factors affect innovators and imitators proportionally; separate permeability indicators for the innovation and imitation components may be considered in future research.

5. Conclusion

The results of the study demonstrate the need to extend the conventional Bass model with regional environmental factors when assessing innovation diffusion in agrocluster systems. Accordingly, innovation permeability coefficients incorporating political, legal, economic, financial, technological, social, environmental, and geographical factors were developed. The effects of these factors on innovation adoption were assessed using the logit model, and an integral indicator was proposed based on these coefficients. Using this indicator, the p and q parameters of the Bass model were modified, enabling the assessment of innovation diffusion dynamics in agroclusters while accounting for environmental influences.

The proposed approach can be used to assess the level of innovative development of agroclusters, forecast innovation diffusion, and identify environmental factors affecting innovation adoption. Further research should focus on empirically testing the model using real agrocluster data, comparing the effects of the coefficients across regions, and evaluating forecasting accuracy.

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