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MODELS OF QUANTITATIVE ESTIMATION OF SOWING DENSITY EFFECT ON MAIZE YIELD AND ITS DEPENDENCE ON WEATHER CONDITIONS

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Abstract

This paper is focused on dependence of corn yield on plant density at harvest time and the influence of weather conditions during crop growth period on the parameters of yield–factor response models. It is established that the main parameters of the models are significantly influenced by both moisture supply (precipitation and water productivity in the soil) and hydrothermal conditions (hydrothermal coefficient and moisture coefficient). The 2016-2018 years are characterized by quite close mathematical relationship (R^2 =0.9672-0.99940) between the corn grain yield and sowing density. It was found the existing dependence of the model parameters on weather conditions and sufficiently high resistance of hybrid DS0493B to external conditions, since the deviation of the values of these conditions has turned out to be much greater than the deviation of the model parameters.

Key words: *maize yield, sowing density, crop modeling, quantitative dependence, water consumption.*

INTRODUCTION

In recent decades, the yield of corn hybrids has increased significantly due to the use of new genotypes and intensification of plant growing technologies (Assefa et al., 2018; Kaminskyi & Asahishvili, 2020). There is no doubt that the density of plants is the main technological factor in the formation of yields, and the optimization of growing conditions of one cultivar or another makes it possible to increase the productivity of both one plant and sowing as a whole (Sarlangue et al., 2007; Liu Y. et al., 2021). This is due to the fact that since the formed yield is a product of the plant photosynthetic activity, it is conceivable that the corresponding area of the leaf surface is formed with each sowing density that is the basis of the process of photosynthesis. It is understood that its intensity will be determined by the above optimization measures. Thus, it can be argued that the density of plants in the field is the basic condition that determines the leaf area duration of the crop, according to the existing conditions of cultivation, the intensity of photosynthesis, and hence the final yield of one plant and sowing (Shapiro & Wortmann, 2006). On the other hand, it is generally known that in sowing there is the competition among plants for space, light, water, mineral nutrients and carbon dioxide (Attia et al., 2021).

There is no doubt that in this case we are talking about clean crops field without weeds, as in other cases there is the competition among crop and weeds (Baer et al., 1984; Mischenko et al., 2019), which are not the subject of study in this work. Having regard to the above, we may talk of the optimal value of plant density. At the same time, according to the rules of agriculture this value is not constant, but depends on the specified growing conditions (moisture, heat, mineral elements, etc.) and the characteristics of the variety or hybrid of this crop (Kharchenko et al, 2019). All the above mentioned reasonably confirm the continued expedience of studying this issue in different soil and climatic zones under different conditions of moisture and fertilizers, new varieties or hybrids, which in general is the basis of varietal farming (Ren et al., 2021; Sher et al., 2017; Yan et al, 2021).

MATERIALS AND METHODS

When examining the above problem in reasonable detail, we should consider the dependence of the yield of one plant (Y_p, g) and the entire sowing (Y_s, t/ha) depending on its density (X, thousand pcs/ha), which is shown in Figure 1 (Kharchenko, 2003).

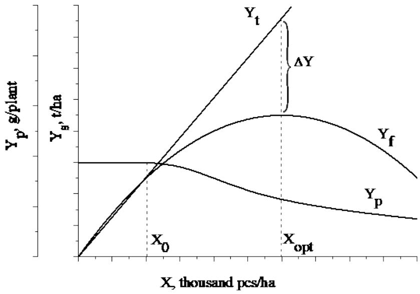

Figure 1. General scheme of dependence of the main crop yields on sowing density

Thus, with certain basic density (X_0), there is no competition in sowing, the yield of one plant has a maximum value, and the yield of the entire sowing may be described by the straight-line dependence of the following type:

$$Y_s = Y_P \cdot X_0 \cdot 10^{-2}, t/ha \quad (1)$$

Further growth in density results in competition, and the closer the sowing is, the more intensive the competition is. The yield of one plant decreases sharply, and the yield of the entire sowing begins to be described by curvilinear dependence. At the same time, the higher the density is, the greater the effect of competition is, and therefore, the greater the deviation of the actual yield from direct dependence is (Fig. 1). It is known that when assessing the yield of the main products (grain, roots), the dependence of yield on density is characterized by a single-humped dome-shaped curve with a salient optimal value of this density. This is due to the fact that if density is more than optimal, the yield of one plant decreases more than the density increases. With some approximation, this dependence may be described by a quadratic parabola without a free term:

$$Y = aX^2 + вX, t/ha \quad (2)$$

where: a and b are empirical coefficients.

Thus, it can be argued that maximum productivity is not formed at the highest value of yield of one plant, but in the conditions when the product of the mass of one plant and density becomes the maximum value. It is clear that this is determined by the nature and intensity of reduction in the mass of 1 plant with increasing density that in turn depends on the competitive ability of sowing itself.

Therefore, in the case of competition in sowing, the actual crop yield is described by curvilinear dependence, and one of the key characteristics of this model is the optimal density value, that is, the density, at which the maximum yield in this series is formed (Fig. 1):

$$X_{opt} = -\frac{в}{2a}, thousandspcs./ha \quad (3)$$

Another important parameter of this model is the value of maximum yield:

$$Y_{\max} = aX_{opt}^2 + bX_{opt}, t/ha \quad (4)$$

Another characteristic indicator of this model, as mentioned above, is the highest density, at which competition in sowing is not observed (X_0) yet and which in general may be the subject of study. At the same time, hypothetically, without competition in sowing, with the known or accepted value of X_0, the theoretical yield (Yt) may be determined by the straight-line dependence (Fig. 1):

$$Yt = (aX_0 + в), \rightleftarrows t/ha \quad (5)$$

The difference (ΔY) between the maximum yield ($Y_{\max}$) and the theoretical yield (Yt) with the optimal density (X_{opt}) enables to determine the indicator of the effect of competition in sowing on the formation of yield (*S, %)* with respect to the theoretical value:

$$S = \frac{100a(X_0 - X_{opt})}{(aX_0 + в)}, \% \quad (6)$$

It is clear that the value (100 – S) is the competitive ability of sowing of this variety in specific weather and technological conditions.

The field experiments on studying the effect of the sowing density on the crop yield were conducted on the experimental fields of the Institute of Agriculture of the North-East of NAAS during 2016 – 2018. The soils were chernozem leached middle loamy on loess with the following basic characteristics: humus content was 4.1–4.7 %, pH_{KCl} = 5.0, easily hydrolysable nitrogen content (by Kornfield) was 112.0, and movable compounds of P_2O_5 and K_2O (by Chirikov) were 118.0 and 100.0 mg/kg, respectively.

The replication of experience was triple. The area of the experimental plot was 28 m^2. The yield was taken into account at humidity of 14%.

The study was conducted with the hybrid DS0493B, which is a product of Dow Seeds Company. The recommended harvesting density is 50-65 thousand plants/hectare (unfavorable conditions); 75-90 thousand plants/hectare (favorable conditions). Yield potential: 15 t/ha.

RESULTS AND DISCUSSIONS

Nowadays, there are many models for predicting the yield of agricultural crops, in particular, corn (Kharchenko et al., 2019). Using linear regression to determine the response to changes in planting density in maize, Assefa et al. (2018) reported that the contribution of plant density to yield increases ranges from 8.5 to 17 %. Using the Bayesian computational methods, Lacasa et al. (2021) have established a significant relationship between crop yield and geographic location, while the planting density and the value of the economic efficiency of growing corn have changed.

Newer corn hybrids have a significant response to nitrogen fertilizers (Sher et al., 2017; Asanishvili et al., 2020; Ciampitti et al., 2021). contents that hybrids with low FAO and lower plant height tolerate high plant densities, increasing the number of grains per area. Taller plants can lodge in dense plantings, and with lower densities, at the same time the diameter of the stem and shoot dry weights increase. The response of hybrids to environmental factors can also be predicted using cluster analysis and cluster diagrams (Palamarchuk et al., 2021).

According to Li et al. (2015), growing corn with drip irrigation and plastic mulching, the yield index, dry matter strongly depended on the plant density ≤4.7 plants per m^2. With an increase in the density of 8.3 plants per m^2, a relationship with the yield index has not been established, but there is an effect on grain yield and dry matter. With an increase in the density of 10.7 or more per m^2, no effect on dry matter has been established, but there was a relationship with a yield index.

Sun et al. (2016), using the APSIM model, which takes into account the variability of weather factors, obtained good predictability of grain yield and corn biomass. According to the data of 11 years of field experience, it has been confirmed that plant density is one of the most important factors that affect corn yield, while plant density correlates with the optimal sowing time.

Shahhosseini et al. (2021) used different calculation models (linear regression, LASSO, LightGBM, random forest, XGBoost) for predicting yields in the corn belt USA. They found that soil moisture is the most influential factor that affects plant phenology. It was proposed to use in modeling such factors as soil water during the growing season and average water table.

Attia et al. (2021) used multivariate analysis, variance decomposition method, Sobol method and proposed their own model for predicting yield. They found that plant biometrics and corn yield were significantly correlated with soil hydrological characteristics, soil fertility, organic carbon content and the phenology of corn depended on the genotype.

Jiang et al. (2021) proposed a new model with spatiotemporally varying coefficient (STVC) that takes into account the spatio-temporal non-stationarity and improves the explanation of the influence of meteorological data on the yield of corn. Khanal et al. (2021), using high-resolution maps with remote sensing technology and modern forecasting equations, has also developed a model that could be applied to access the effect tillage, fertilization and yield with high accuracy.

Pepeliaev et al. (2020) propose a quantile regression method for yield modeling depending on climatic parameters for the central region of Ukraine. NDVI with polynomial regression analysis, Slant Range, Mathcad, stress index is also used for accurately crop yield predicting (Pasichnyk et al., 2019; Pasichnyk, 2020; Serdiuchenko et al., 2019). NDVI recommended to be determinate during silking (VI) and flowering (R1) (Vozhehova et al., 2020).

The use of different models for predicting corn yields depending on weather conditions shows large discrepancies that need to be processed by a larger database (Yin & Leng, 2021; Drobitko et al., 2020).

The regression and correlation analysis in our research has made it possible to form mathematical models of yield dependence on sowing density and to determine their reliability (Table 1).

Table 1. Effect of sowing density on the grain yield of DS0493B maize hybrid

Year	Density, thousand pcs/ha		Actual yield (average), t/h	Yield-density model	Determination coeffi-cient, R^2
	after germination	during harvesting			
2016	60	57.1	11.8	$Y = -0.00202X^2 +0.30978X$	0.96720
	70	61.4	10.7		
	80	71.4	11.7		
	90	81.4	12.0		
2017	60	56.1	10.5	$Y = -0.00233X^2 +0.32008X$	0.99940
	70	64.6	11.1		
	80	78.4	10.8		
	90	82.2	10.5		
2018	60	56.5	9.2	$Y = -0.00209X^2 +0.27220X$	0.98575
	70	62.6	8.4		
	80	77.7	8.2		
	90	85.1	8.3		

A graphic illustration of the obtained models is shown in Figure 2.

These data indicate a significant difference between the above parameters of the generated models. Thus, if in the conditions of 2016 the optimal density (X_{opt}) and the maximum yield (Y_{max}) had the largest values, in 2018 – the lowest (respectively 76.7 and 65.1 thousand pcs/ha and 11.88 and 8.86 t/ha) with an intermediate value in 2017 (Table 2).

On average, over the three years the optimum plant density amounted to 70.2 thousand pcs/ha and the maximum yield was equal to 10.58 t/ha.

Usanova et al. (2019) reports the optimal data and the highest net income was obtained at a plant density of 100 thousand plants per hectare. Different hybrids respond differently to changes in environmental and soil conditions (Usanova & Migulev, 2019). Semina et al. (2018) results show that the greater the plant density, the lower the amount of grain in the cob (by 8.1-21.1% - on leached heavy loamy chernozems).

The problem of uncertainty of the value of the basic density (X_0) rises from the estimation of the indicator of competition in sowing (S, %), or competitive ability of sowing (100-S). Since this value has not been studied experimentally, this paper contains the proposal that its analytical determination should be made provided that at optimal density the competition indicator is about 45% (Kharchenko, 2003).

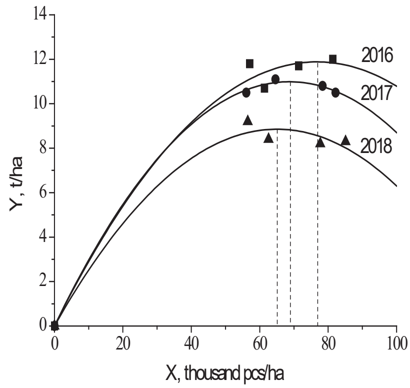

Figure 2. Models of response of yield of hybrid maize DS0493B on plant density by the study years

2016: $У = -0.00202 X^2 + 0.30978X$ $R^2 = 0.98729$

2017: $У = -0.00233 X^2 + 0.32008X$ $R^2 = 0.99940$

2018: $У = -0.00209 X^2 + 0.27220X$ $R^2 = 0.98575$

Table 2. Parameters of Yield – Density Models of DS0493B maize hybrid (according to the data obtained during 2016-2018)

Indicators	Years			Average
	2016	2017	2018	
Optimal sowing density (X_{opt}), thousand pcs/ha	76.7	68.7	65.1	70.2
Maximum yield (Y_{max}), t/ha	11.88	11.00	8.86	10.58
Basic sowing density, thousand pcs/ha (at S – 45 %)	13.95	12.53	11.84	12.77

Thus, the dependence 6 results in the following:

$$X_0 = \frac{100a \cdot X_{opt} + P \cdot в}{(100-P)a}, thousand \rightleftarrows pcs/ha \qquad (7)$$

The calculations have shown that the density of sowing, at which competition begins, ranges from 13.95 thousand pcs/ha (2016) to 11.84 thousand pcs/ha (2018) with the average value of 12.77.

All of the above suggest significantly different conditions for the formation of yield in those years. At the same time, there is no doubt that since the main parameters of the models had the best values in the conditions of 2016, these conditions may be considered to be the most favorable.

It is well known that one of the main factors of crop growth and development and, therefore, the formation of yield, or weather conditions, is the moisture resource. At the same time, the estimation of availability of this resource may be carried out both by the growing season of the crop and its individual parts (Polevoy, 2007). It is the estimation of the conditions by the provision of moisture resources that may be made both in terms of precipitation amount and the full resource of this factor that is the amount of precipitation for a specific period (A, mm) and moisture reserves (productive) in the established or accepted soil layer at the beginning of this period (MP, mm).

It has been established that the conditions of natural moisture of the vegetation periods of maize during the study years are significantly different. Thus, according to the amount of precipitation at a rate of 254 mm (Logvinova et al., 1976), the actual values ranged from 403.7 mm in 2016 to 118.7 mm in 2018 with a deviation from the norm of +148.3 to -135.3 mm. The moisture reserves in the meter layer of soil during germination were 175.0-36.6 mm with an average value of 154.0 mm (Logvinova et al., 1976). In general, the moisture provided to the crop (initial moisture reserves together with the actual precipitation) for the years ranged from 578.7 to 271.1 mm, that is, the deviation from the long-term average annual (408.0) ranged from +170.7 to – 137.9 mm.

There is no doubt that the estimation of the conditions for the formation of the maize yield cannot be complete without taking into account the resource of such factor as heat, which is determined by the sum of active air temperatures. In addition, it is notorious that a significant indicator of the characteristics of the growing season is hydrothermal conditions, which includes various combinations of moisture and heat resources. The most common indicators of hydrothermal conditions are the hydrothermal coefficient of Selianinov H. T. (HTC) (Logvinova et al., 1976) and the coefficient of moisture of Bova N. V. (Chirikov, 1986). Thus, it is established that with average long-term value of HTC equal to 1.13 for the years of research it was 0.91 with fluctuations during the years from 1.62 to 0.44. Therefore, the above makes it possible to assert that the weather conditions of 2016-2018 were somewhat drier than normal, and the actual conditions ranged from wet (2016) to very dry (2017 and 2018). Similarly, the conditions are characterized by the coefficient of moisture. The results of comparison of the key characteristics of the proposed models and various indicators of the characteristics of the conditions are given in the Table 3.

Table 3. Comparative characteristics of the basic parameters of the Yield – Density Model and indicators of the conditions of the maize growing season

Indicators	Years			Average value for three years	Long-term average annual
	2016	2017	2018		
Optimal sowing density (X_{opt}), % in relation to 2016	100	89.6	84.9	–	–
Maximum yield (Y_{max}), % in relation to 2016	100.0	92.6	74.6	–	–
Basic sowing density, % in relation to 2016	100	89.8	84.9	–	–
Precipitation for May - August ($\sum A$), mm	403.7	157.2	118.7	226.5	254.0
In relation to 2016, %	100.0	38.9	29.4	–	–
Proposed moisture resource ($\sum A$ + MP), mm	578.7	293.8	271.1	381.2	408.0
In relation to 2016, %	100.0	50.7	46.8	–	–
Sum of active temperatures ($\sum t\ ^0C$)	2487	2332	2680	2500	2241
In relation to 2016, %	100.0	93.8	107.8	–	–
Hydrothermal coefficient ($HTC = \frac{\Sigma A}{0,1\Sigma t}$)	1.62	0.67	0.44	0.91	1.13
In relation to 2016, %	100.0	41.3	27.2	–	–
Coefficient of moisture ($Cm = \frac{\Sigma A+MP}{0,1\Sigma t}$)	2.32	1.26	1.01	1.52	1.82
In relation to 2016, %	100.0	54.3	43.5		

Comparing the fluctuations of the basic parameters of the Yield – Density Model by years and the actual conditions of the growing period of these years, it can be argued that there is a fairly close relationship between them. However, it should be noted that this hybrid maize is relatively resistant to changes in weather conditions. Thus, if the deviation of the values of the established parameters of the conditions by years from the conditions of 2016 range from 51.2% (A+MP) to 72.8 (HTC), the fluctuations of the model parameters do not exceed 25.4 (Y_{max}).

So, the climate is changing and the analysis of parameters of soil temperature, humidity, precipitation should be taken into account in planning crop yields (Maltais-Landry & Lobell, 2012; Rusu et al., 2013; Iizumi, 2017; Maxim et al., 2018; Pasca & Rusu, 2018).

CONCLUSIONS

Regression and correlation analysis allowed to make mathematical models of yield dependence on sowing density and to determine their reliability. A close mathematical relationship of reaction of maize grain yield to plant density (R^2 = 0.9672 – 0.99940) was observed during all the years of research.

The sowing density at which competition begins ranged from 11.84 to 13.95 thousand units/ha in 2016-2018 (in average 12.77). Rather close dependence of parameters of the specified models on weather conditions of the crop growing period has been determined.

It is proved that under the conditions of 2016-2018, the hybrid maize DS0493B turned out to be quite resistant to external conditions, since the deviation of values of these conditions was much greater than the deviation of parameters of the models.

The proposed models could help in determination of the impact of competition between plants on the yields, calculate the optimal value of the density at which the maximum yield is formed.

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