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Utilizing Remote Sensing Data to Ascertain Weed Infestation Levels in Maize Fields

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Abstract: This study presents the evaluation of tools for weed analysis and management to support agroecological practices in organic farming, emphasizing agriculture digitalization and remote sensing. The main aim was to provide techniques for monitoring and prediction of weed spread using multispectral satellite and drone data, without the use of chemical inputs. Key findings indicate that VV and VH channels of Sentinel-1 and B2, B3, B4 and B8 channels of Sentinel-2 are not different regarding tillage, herbicide use, or sowing density. However, RE and NIR channels of drone detected significant variations and proved effectiveness for weediness monitoring. The NIR channel is sensitive to agrotechnical factors such as cultivation type, making it valuable for field monitoring. Correlation and regression analyses revealed that B2, B3, B8 channels of Sentinel-2 and RE and NIR drone channels are the most reliable for predicting weed levels. Conversely, Sentinel-1 showed limited predictive utility. Random effect models confirmed that Sentinel-2 and drone channels can accurately account for site characteristics and timing of weed proliferation. Taken together these tools provide effective organic weed monitoring systems, enabling rapid identification of problem areas and adjustments in agronomic practices.

Keywords: Agroecological farming; Digitalization; Drone; Herbicide; Organic agriculture; Sentinel; Weediness

1. Introduction

Effective weed management is an important component of sustainable agricultural development in modern organic farming [1]. Organic production requires strong reduction or complete avoidance of the use of chemical herbicides, that stimulates development of alternative, environmentally safe methods of weed control [2–5]. The use of remote sensing (RS) data in precision agriculture is an important tool in modern agronomic management. Using RS technologies and geospatial data processing, it becomes possible to conduct accurate monitoring of the state of crops. Such analysis of images from Sentinel-1 and Sentinel-2 satellites and data from drones opens new opportunities for monitoring vegetation, including the assessment of the weediness [6].

RS data might be also used to identify areas with extensive weediness and analyze the effectiveness of herbicide-free agrotechnical methods. Remote sensing is the basis of modern approaches [7,8]. The use of spectral data from satellites or drones allows the analysis of light reflectance by vegetation in near-infrared (NIR) and mid-infrared (MIR) spectral ranges. In addition, the distribution of spectral reflectance can serve as useful indicator of different types of vegetation, including weeds [9–11].

The use of vegetation indices such as Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI) and Green Normalized Difference Vegetation Index (GNDVI) showed high efficiency in separating weeds from crops [12–16]. Recent advances in machine learning and artificial intelligence have significantly improved the accuracy of weed identification [17,18].

Algorithms such as Random Forest, Support Vector Machines (SVM) and neural networks are effectively used to analyze large amounts of RS data [18–21].

Maize is extensively used in such type of studies because it is one of the key agricultural crops where accurate determination of weed infestation level is critical to ensure high yields. According to earlier studies, the spectral properties of weeds are significantly different from those of maize, which allows effective RS using for their identification [10,22,23]. The use of unmanned aerial vehicles (UAVs) and satellite imagery combined with high-precision indices allows for the assessment of weed infestation levels over large areas with minimal cost [24–26].

Organic production of maize requires a tool that helps predict weed levels based on historical data. The model, which includes the coefficient of weediness such as integrated indicator that considers the density and height of grass, broadleaf, and root weeds, can be the basis for planning agrotechnical measures. This makes possible to evaluate the effectiveness of weed control measures and to improve management systems in agroecological farming. Thus, the goal of present study was to develop and substantiate new approaches to weed management based on agriculture digitalization and RS technologies. The study was designed in the way to evaluate the possibilities of analyzing the state of weeding using multispectral images from satellites and drones, to identify key factors affecting the level of weeding, and to create a model that will allow effective monitoring and forecasting of weeding without the use of chemicals.

The outcomes of using remote sensing and drone data may be very different, though, depending on the crop being analyzed, the processing technologies, the density of the plantation, and other technological factors. Therefore, we elucidated the potential applications of Sentinel-1, Sentinel-2, and drone images taken at different spectral channels in determining the extent of weed infestation in areas with varying plowing methods, sowing density, and natural protection, among other factors.

2. Materials and Methods

Key characteristics of experimental field. The experimental plot was a part of larger the experimental field of the Polissia National University (N 50°26′; E 28°42). The site has predominantly Gleic Albic Luvisol (Endoclayic, Cutanic, Differentic, Katogleyic, Ochric type of soil according to WRB (2022).

Weather conditions significantly affect the quality of space or drone shooting and shooting from drones, it should be noted that the weather of research area is moderately continental with humid conditions. The average annual air temperature is about 7–8 °C, and the average temperature in January is about 5 °C. The summer temperature usually ranges between 18–20 °C. The amount of precipitation varies between 600–700 mm per year, with the most part falling in the summer period. The relative humidity of the air is significantly raised.

Analysis of variance is used to evaluate the effects of factors F1, F2, F3, and their interactions. Experiment was tested in three replications to minimize experimental error and improve result validity.

Plot of about 1 hectare was divided into 12 experimental plots with three replications (Figure 1). The research employs a factorial experimental design where F1, F2, F3 were combined. Each combination of F1 × F2 × F3 was implemented in three replicates. The study explored the impact of the following factors: F1 - tillage systems: S1- deep soil plowing on 18–20 cm (standard), S2 – soil disking on 10–12 cm (AES), S3 – soil milling on 5–7 cm (AES); F2 – sowing density: A1 – 1.1 sowing units/ha (standard); A2 – 1.3 sowing units/ha (AES); F3 - herbicide application: H1 – herbicide application (standard); H2 - herbicide nonapplication (AES).
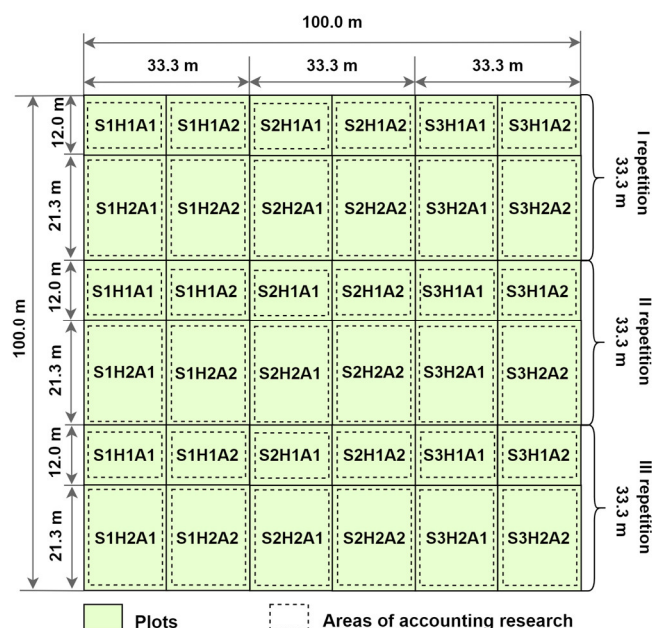
Figure 1. Experiment design.

Data were collected with a frequency of one week using each source. During field research, the parameters of main crops, cereal weeds, broadleaf, and short-leaved weeds were measured by height and density for each plot.

To conduct aviation research copter-type DJI Mavic 3M drone was used with a multispectral camera of the following characteristics: image sensor – 1/2.8-inch CMOS, effective pixels: 5 Mn; Lens – FOV: 73.91° (61.2° x 48.10°); equivalent focal length – 25 mm; aperture – f/2.0; fixed focus; image format – TIFF; video resolution – H.264 FHD: 1920 x 1080@30 fps.

Images were obtained in the following spectral ranges based on the results from aerial photography: Green (G): 560 ± 16 nm; Red (R): 650 ± 16 nm; Red Edge (RE): 730 ± 16 nm; Near infrared range (NIR): 860 ± 26 nm. We determined the average values of radiation intensity in the specified spectral ranges, made calculations, and determined the average values of the NDVI vegetation index for each site over a five-week time interval during the geoinformation analysis of the obtained images.

Space research was conducted using data received from the Sentinel-1 and Sentinel-2 spacecraft. During Sentinel-1 measurements, space images were obtained in the radio wave range in the IWS mode with a resolution of 5 x 5 m, a bandwidth of 20 x 20 km with VV and VH polarization. As a result of data processing, the average values of the radiation intensity for the middle of each section were determined.

The reception of images from the Sentinel-2 optical-electronic observation spacecraft was carried out in the Band 2 (Blue) spectral ranges of 490 nm; Band 3 (Green) 560 nm; Band 4 (Red) 665 nm; Band 8 (NIR) 842 nm. The processing of the data from the space shooting was carried out according to the methodology like the processing of the data from the aerophotography by spectral channels with the determination of the vegetation index NDVI.

Database description. To effectively conduct the experiment, we formed a panel database that incorporated the results of physical examinations of plants and soil, data from the Sentinel-1 and Sentinel-2 satellites, and indicators from a drone. We collected data for five time points at each experimental site. This ensures the two-dimensionality of the data, enabling the analysis of the object individual features and their changes over time. Additionally, we ensured the stability of the sample when forming the panel database. Observation took place in the same areas, which do not change over time in terms of size and type of observation.

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The object of the sample was 36 plots, which were formed from one experimental field where maize was sown. The database formation process provides the sample depth, which determines the number of observations for a specific researched field. Indeed, we observed each of the 36 sites five times. Three indicators determine the type of plot cultivation, ten indicators stem from a visual survey, six indicators derive from data from the Sentinel-1 and Sentinel-2 satellites, five indicators come from a drone survey of experimental plots, and the remaining indicators come from soil tests at the experimental site (Table 1).

Table 1. Database indicators.

A group of indicators	Indicators
Type of processing	Tillage_sy, Herbicides, Sowing_den
Visual examination	Maize_height_cm, Maize_density_m2, Grass_weeds_number, Grass_weeds_density_m2, I_Dicotyledoneae_weeds_number, I_Dicotyledoneae_weeds_density_m2, II_Dicotyledoneae_weeds_number, II_Dicotyledoneae_weeds_density_m2, Root_weeds_number, Root_weeds_density_m2, Int_weed
Satellite data	VV, VH, B2, B3, B4, B8
Drone data	G, R, RE, NIR, NDVI

Data from various sources, including space and drone images, were processed as shown in Figure 2. The NDVI coefficients were used to create models that help identify how weedy the crops are. The measurements were carried out 5 times at different phases of the maize plant development.

A   B   C
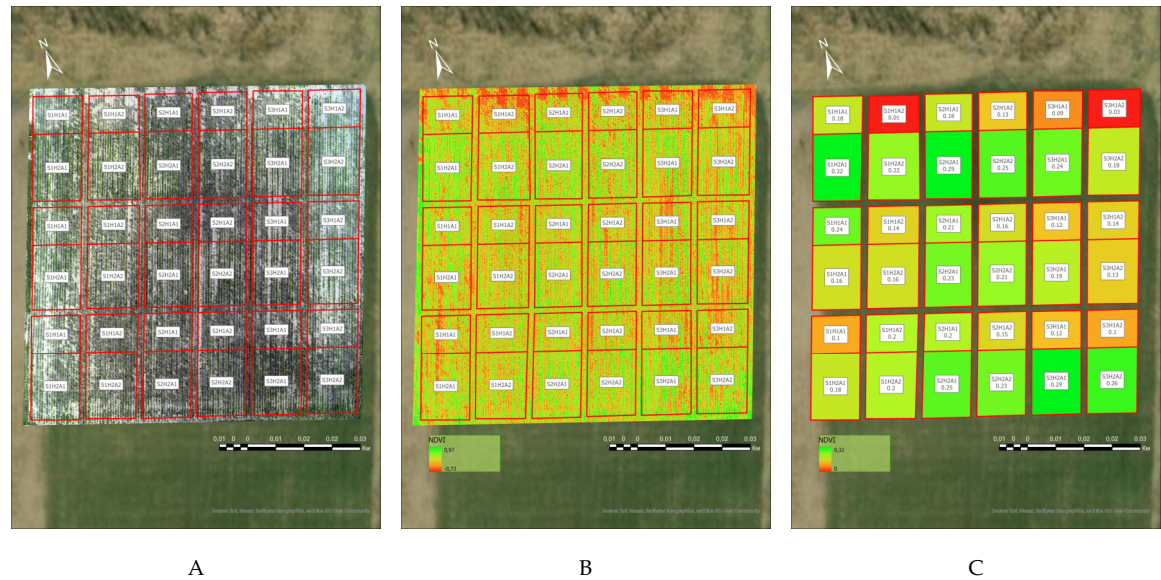
Figure 2. The procedure for processing space images and images from drones. Flowering stage (shooting from a drone DJI Mavic 3M). A - image in pseudo-color; B - NDVI coefficient per pixel distribution; C - averaged values of the NDVI coefficient by fields.

Consequently, the database using 8460 unique indicators for each research area was formed.

3. Results

3.1. Employing Satellite and Drone Imagery for Weed Identification

Since organic farming does are pesticide-free, effective weed management is crucial to ensuring high yields. Using agroecological methods like changing tillage practices, adjusting planting density, and adding natural pest controls might significantly affect weed growth.

However, regional conditions often determine the effectiveness of these methods, this requires accurate measurements that are taken often. That can only be done by ground monitoring. Modern RS methods, like images from Sentinel-1 and Sentinel-2 satellites and data from drones, allow for rapid checks of field conditions. This research aims to find out if RS data can show how different farming methods, natural materials, and planting amounts affect crops, and if images from Sentinel-1, Sentinel-2, and drones can show these differences.

ANOVA was used to determine the differences in VV, VH, B2, B3, B4, B8, G, R, RE, and NIR channels within different types of tillage (*Tillage_system*), herbicide application (*Herbicides*), and sowing density (*Sowing_density*) (Table 2). An ANOVA test was used to see how important each factor was in the channels and to see if this information can be used to keep track of weediness levels in organic farming.

Table 2. Variance analysis (ANOVA) for all channels of Sentinel-1, Sentinel-2 and drones for weed detection.

Channel	Df	Sum	Sq Mean	Sq F	Value	Pr(>F)
VV	*Tillage_system*	2	17.4	8.715	1.872	0.157
	Herbicides	1	2.0	1.990	0.427	0.514
	Sowing_density	1	4.2	4.248	0.912	0.341
	Residuals	175	814.9	4.656		
VH	*Tillage_system*	2	18.1	9.073	1.045	0.354
	Herbicides	1	1.3	1.305	0.150	0.699
	Sowing_density	1	1.5	1.528	0.176	0.675
	Residuals	175	1519.7	8.684		
B2	*Tillage_system*	2	49854	24927	0.991	0.373
	Herbicides	1	2102	2102	0.084	0.773
	Sowing_density	1	5571	5571	0.221	0.639
	Residuals	175	4403990	25166		
B3	*Tillage_system*	2	109883	54942	1.550	0.215
	Herbicides	1	10554	10554	0.298	0.586
	Sowing_density	1	9437	9437	0.266	0.606
	Residuals	175	6201606	35438		
B4	*Tillage_system*	2	255469	127734	0.963	0.384
	Herbicides	1	8563	8563	0.065	0.800
	Sowing_density	1	29341	29341	0.221	0.639
	Residuals	175	23207253	132613		
B8	*Tillage_system*	2	485977	242989	1.577	0.209
	Herbicides	1	129754	129754	0.842	0.360
	Sowing_density	1	16495	16495	0.107	0.744
	Residuals	175	26958475	154048		
G	*Tillage_system*	2	22183221	11091610	6.184	0.003
	Herbicides	1	1141370	1141370	0.636	0.426
	Sowing_density	1	56954	56954	0.032	0.859
	Residuals	175	313870661	1793547		
R	*Tillage_system*	2	13020158	6510079	2.849.	0.061
	Herbicides	1	18115158	18115158	7.927	0.005

		Df	Sum Sq	Mean Sq	F value	Pr(>F)
	Sowing_density	1	1577901	1577901	0.690	0.407
	Residuals	175	399912227	2285213		
RE	*Tillage_system*	2	1740347	870174	0.313	0.732
	Herbicides	1	14970699	14970699	5.381	0.022
	Sowing_density	1	337323	337323	0.121	0.728
	Residuals	175	486873488	2782134		
NIR	*Tillage_system*	2	15326079	7663039	11.86	<0.001
	Herbicides	1	18277361	18277361	28.29	<0.001
	Sowing_density	1	6644403	6644403	10.29	0.002
	Residuals	175	113050243	646001		

Df – degrees of freedom for each factor and residual values; Sum Sq – sums of each factor squares; Mean Sq – average squares; F value – the value of the F-statistic for each factor; Pr(>F) – p-value that allows to assess whether the effect of a factor is statistically significant.

Consequently, the use VV and VH channels of Sentinel-1 for all three factors, reveals no changes. This indicates that these tools are not sufficiently effective for discerning variations in tillage systems, sowing density, and the application of herbicides. We also identified no statistically significant variations concerning all this factors for the Sentinel-2 channels. Sentinel-2 channels demonstrate restricted sensitivity to differing tillage practices and planting techniques.

Using G, R, RE, NIR drone channels to study tillage systems shows a significant difference (p = 0.003) indicating that the tillage system has a strong effect. Herbicide application and sowing density are not statistically significant. Variation in the R channel showed substantial impact of herbicide application with suggesting a possible impact of tillage (p = 0.061).

The RE channel related to herbicides is significant (p = 0.022), demonstrating the impact of herbicide treatment, and three factors are statistically significant for NIR channel: tillage system (p < 0.001), herbicides (p < 0.001), and sowing density (p = 0.002). Thus, the NIR drone channel is the most sensitive and appropriate for detecting of all three agrotechnical parameters effects.

Thus, we can conclude, that the VV and VH channels of Sentinel-1 did not yield statistically significant findings for any of the three criteria, rendering them less useful in discerning differences. We found the same results for bands 2, 3, 4 and 8 of Sentinel-2; these channels also do not show any significant impact on tillage, herbicide, and sowing density parameters.

The G drone channel exhibited sensitivity to the processing method employed. Channel R demonstrated importance for herbicides and approached significance about tillage system, while RE is significant solely for the herbicide component. The NIR channel is the most informative and exhibits high sensitivity to all three parameters, rendering it the most promising for weed monitoring.

3.2. Estimation the Weediness Level in Maize Based on Sentinel-1, Sentinel-2 and Drone Images

This study aims to find out if RS images from these sources can be used to check weed levels by using information from different channels. To meet this goal, we used the same dataset as in 3.1.

To accomplish this, we computed the weed index (WI), a composite metric that considers the density and height of various weed species. Regression analysis was employed to assess the data and estimate the value of the RS channels of the landscape concerning the integrated WI, defined as the cumulative product of the height of all weed species on their projective coverage. Following the formulation of the WI variable, defined as:

WI = (grass weeds, quantity × grass weeds density, m²) + (I Dicotyledoneae weeds, quantity × I Dicotyledoneae weeds density, m²) + (II Dicotyledoneae weeds, quantity × I Dicotyledoneae weeds density, m²) + (Root weeds, quantity × Root weeds density, m²).

A correlation and regression analysis were conducted between Sentinel-1, Sentinel-2, and drone channels and the level of weediness.

Table 3. Correlation analysis between the channels and the level of weediness.

Channel	Weed correlations
VV	0.1165
VH	0.1365
B2	-0.4276
B3	-0.3307
B4	-0.3584
B8	0.3993
G	-0.1821
R	-0.2347
RE	-0.2440
NIR	0.4007

Residuals:Min -416.48, 1Q -116.54, Median -13.84, 3Q 70.59, Max 886.84.

Sentinel-1: channels VV and VH have a weak correlation with WI (0.116 and 0.137, respectively). Channels B2, B3, B4, and B8 of Sentinel-2 exhibit an average correlation level, with B2 (-0.428) and B8 (0.399) being the most informative. The RE drone channel (-0.244) and the NIR channel (0.401) have a more robust correlation with the weediness score, signifying their substantial informativeness (Table 3).

The combined regression "*Weed_model*" reveals that B2, B3, B8, RE, and NIR are significant channels, with a p-value <0.05 (Table 4). Coefficient of determination: R^2 = 0.5406, indicating that the model explains approximately 54% of the variation in *weed_index*.

Table 4. Regression analysis for Sentinel-1, Sentinel-2, and drone channels.

Channel	Estimate Std. Error	t	value	Pr(>|t|)
(Intercept)	4281.867	1229.373	3.483	0.001
VV	0.154	8.950	0.017	0.986
VH	-18.581	7.300	-2.545	0.012
B2	-9.145	1.070	-8.549	<0.001
B3	8.481	1.449	5.853	<0.001
B4	-0.977	0.648	-1.509	0.133
B8	-0.358	0.108	-3.326	0.001
G	-0.033	0.047	-0.687	0.493
R	0.020	0.044	0.451	0.652
RE	0.033	0.013	2.570	0.011
NIR	0.052	0.027	1.938	0.054

Residual standard error: 206.5 on 169 degrees of freedom. Multiple R-squared: 0.5406,   Adjusted R-squared: 0.5134. F-statistic: 19.89 on 10 and 169 DF, p-value: < 0.001.

Table 5. The Weed model.

Residuals:		Channel	Coefficients:			
			Estimate Std. Error	t	value	Pr(>|t|)
		Call: lm(formula = weed_index ~ VV + VH, data = data)				
Min	-313.04	(Intercept)	573.463	149.268	3.842	<0.001
1Q	-171.20	VV	8.906	11.682	0.762	0.447
Median	-81.68	VH	10.543	8.618	1.223	0.223
3Q	51.15					
Max	1426.12	Residual standard error:	294.5 on 177 degrees of freedom			

		Multiple R-squared:		0.022	
		Adjusted R-squared:		0.011	
		F-statistic		1.977 on 2 and 177 DF	
		p-value		0.142	

Call: lm(formula = weed_index ~ B2 + B3 + B4 + B8, data = data)

Min	-353.10	(Intercept)	4144.249	1084.508	3.821	<0.001
1Q	-132.90	B2	-7.851	0.828	-9.485	<0.001
Median	-25.40	B3	8.226	1.323	6.217	<0.001
3Q	103.00	B4	-1.365	0.597	-2.288	0.023
Max	971.00	B8	-0.366	0.090	-4.046	<0.001

Residual standard error:		218.6 on 175 degrees of freedom
Multiple R-squared:		0.467
Adjusted R-squared:		0.455
F-statistic		38.370 on 4 and 175 DF
p-value		<0.001

Call: lm(formula = weed_index ~ G + R + RE + NIR, data = data)

Min	-498.25	(Intercept)	-845.610	400.432	-2.112	0.036
1Q	-144.68	G	-0.050	0.057	-0.874	0.383
Median	-47.57	R	0.047	0.054	0.880	0.380
3Q	61.73	RE	-0.046	0. 013	-3.705	0.000
Max	1319.33	NIR	0.152	0.030	5.046	<0.001

Residual standard error:		261.2 on 175 degrees of freedom
Multiple R-squared:		0.239
Adjusted R-squared:		0.222
F-statistic		13.73 on 4 and 175 DF
p-value		<0.001

The Sentinel-1 model shows a very weak connection between changes in weediness and the VV and VH channels, with a correlation value of $R^2 = 0.0218$. Therefore, we can deduce that the VV and VH channels are not useful for weediness evaluation.

Weediness changes in Sentinel-2 channels demonstrate statistical significance ($p < 0.05$), and $R^2 = 0.467$, indicate a strong correlation between the Sentinel-2 and WI channels. Consequently, the Sentinel-2 channels, particularly B2 and B3, are indicative for forecasting weed density.

The models created with data from drones identified important channels, specifically RE and NIR, with a $p < 0.05$. The coefficient of determination $R^2 = 0.239$ signifies the reasonable efficacy of the model utilizing drone channels for forecasting WI.

Consequently, the RE and NIR channels substantially indicate the weediness level, validating their appropriateness for monitoring.

The RE and NIR channels greatly affect how we measure weediness, proving they are useful for monitoring. All Sentinel-2 channels, RE and NIR drones channels exhibit the strongest association with weediness levels and show potential for predictive applications. Channels Sentinel-1 has shown little utility and is not advisable for application in weed assessment models.

The model that uses the best channels, especially B2, B3, RE, NIR, can accurately predict weed growth, which will help agroecological farming.

3.3. RS Factors for the Model Construction of Weediness

Models have to consider the unique characteristics of each plot and the individuality of temporal observations; thus, the addition of random effects (plm) is essential.

The Table 6 displays the outcomes of modeling the assessment of weediness in maize crops utilizing the Sentinel-1 VV and VH channels. In research modeling, random factors account for the unique weediness features of each plot and the temporal specificity of observations. The coefficient values for VV and VH, similar to prior tasks of this study, were not statistically significant (p-value for VV = 0.446 and for VH = 0.221), indicating a modest correlation between these channels and weediness. R^2 = 0.0218, indicating a minimal capacity to explain differences in weediness levels.

Table 6. Model for assessing the weediness of maize crops with VV and VH channels of Sentinel-1 (Random Effect Model with Swamy-Arora's transformation, one-way individual effect).

Call: plm(formula = weed_index ~ VV + VH, data = pdata, model = "random")						
Effects:		Var	Std. dev	Share		
idiosyncratic		91096.6	301.8	1		
individual		0.0	0.0	0		
theta:		0				
Residuals:		Channel		Coefficients:		
			Estimate, S	Std. Error	z-value	Pr(>|z|)
Min	-313.04	(Intercept)	573.463	149.268	3.842	0.000
1Q	-171.20	VV	8.906	11.682	0.762	0.446
Median	-81.68	VH	10.543	8.618	1.223	0.221
3Q	51.15					
Max	1426.12	Total Sum of Squares:			15692000	
		Residual Sum of Squares:			15349000	
		R-Squared:			0.022	
		Adj. R-Squared:			0.011	
		Chisq			3.953 on 2 DF	
		p-value			0.139	

As a result, the Sentinel-1 channels (VV and VH) do not provide sufficient information to forecast weediness assessments.

The model used to detect weeds in maize fields with Sentinel-2 indicators (B2, B3, B4, B8) showed that all channels are important (p < 0.05), meaning they strongly relate to the amount of weed infestation (Table 7).

Table 7. Model for determining weed infestation in maize based on Sentinel-2 channel indicators (Random Effect Model with Swamy-Arora's transformation, one-way individual effect).

Call: plm(formula = weed_index ~ B2 + B3 + B4 + B8, data = pdata, model = "random")						
Effects:		Var	Std. dev	Share		
idiosyncratic		43020.5	207.4	1		
individual		0.0	0.0	0		
theta:		0				
Residuals:		Channel		Coefficients:		
			Estimate, S	Std. Error	z-value	Pr(>|z|)
Min	-353.061	(Intercept)	4144.249	1084.508	3.8213	0.000
1Q	-132.924	B2	-7.851	0.828	-9.4850	<0.001
Median	-25.397	B3	8.226	1.323	6.2167	<0.001
3Q	102.976	B4	-1.365	0.597	-2.2881	<0.001
Max	970.953	B8	-0.366	0.090	-4.0457	<0.001

Total Sum of Squares:	15692000
Residual Sum of Squares:	8359900
R-Squared:	0.467
Adj. R-Squared:	0.455
Chisq	153.486 on 4 DF
p-value	<0.001

There is a strong negative relationship between weed_index and channel B2 (S = -7.85, p < 0.001). A substantial positive correlation was identified for B3 (S = 8.23, p < 0.001). The data from channels B4 and B8 are statistically significant as well, and R^2 = 0.467 signifies a satisfactory capacity to reflect fluctuations in weediness levels.

Consequently, Sentinel-2 channels, particularly B2 and B3, serve as crucial indicators for weediness evaluation, rendering this set of channels appropriate for prediction.

Table 8. Model to determine the weediness of maize crops with drone channel indicators (Random Effect Model with Swamy-Arora's transformation, one-way individual effect).

Call: plm(formula = weed_index ~ G + R + RE + NIR, data = pdata, model = "random")					
Effects:	Var	Std. dev	Share		
idiosyncratic	61203.4	247.4	1		
individual	0.0	0.0	0		
theta:	0				
Residuals:		Channel	Coefficients:		
			Estimate, S	Std. Error	z-value	Pr(>|z|)
Min	-498.25	(Intercept)	-845.611	400.432	-2.112	0.0350
1Q	-144.68	G	-0.050	0.057	-0.874	0.3820
Median	-47.57	R	0.047	0.054	60.880	0.3790
3Q	61.73	RE	-0.046	0.013	-3.705	0.0000
Max	1319.33	NIR	0.152	0.030	5.047	<0.001

Total Sum of Squares:	15692000
Residual Sum of Squares:	11943000
R-Squared:	0.239
Adj. R-Squared:	0.222
Chisq	54.932 on 4 DF
p-value	<0.001

The method for checking weeds in maize crops using drone channels showed that the data of RE and NIR channels are significant. RE exhibits a substantial negative correlation with WI (S = -0.046, p < 0.001), while NIR demonstrates a considerable positive correlation (S = 0.152, p < 0.001). The data from the G and R channels did not exhibit a significant correlation with the weediness indices of maize crops. The coefficient of determination R^2 = 0.239, signifying a moderate capacity to reflect fluctuations in weediness levels. Consequently, the RE and NIR channels from drones are proficient in evaluating the degree of weediness.

Thus, the B2 and B3 Sentinel-2 channels and RE and NIR drone channels are the most informative approach for indicating the weediness level. Sentinel-1 channels did not show a statistically significant relationship with the level of weediness and are probably less useful for this task. The most promising channels can be used to develop a monitoring system that will allow effective management of weeding within the framework of agroecological farming.

5. Conclusions

In this study, we assessed several key parameters employing satellite and drone imagery for weed identification and estimation of weediness level in maize fields.

The obtained results indicated that RE and NIR drone channels effectively identified substantial changes and are more sensitive to all three factors, which makes it the best choice for weed identification. The NIR channel sensitivity to agrotechnical aspects, such as cultivation type, rendering it advantageous for field monitoring. Sentinel-1 and Sentinel-2 channels exhibit no statistical changes concerning the three investigated factors.

Correlation and regression analysis indicate that B2, B3, B8 Sentinel-2 channels and RE, NIR drone channels have the strongest association with weediness, yielding precise forecasts of weediness levels. Conversely, Sentinel-1 channels exhibited minimal correlation and significance, suggesting its restricted utility for weed prediction.

Panel models of random effects indicated that B2 and B3 channels of Sentinel-2, RE and NIR channels of drone were the most informative for prediction of weediness. They guarantee the precision of predictions by considering the unique attributes of each location and the temporal variations in weed proliferation. These channels can serve as the foundation for developing an efficient weed monitoring system for organic agriculture, enabling the prompt detection of problematic regions and the adjustment of agronomic practices.

6. Patents

Utility model patent No. 158094 (UKR) Station for Receiving Information from Space Apparatus for Remote Sensing of the Earth. https://iprop-ua.com/inv/3tjnh0sz/

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