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Study of Land Quality and Land Characteristics that Determine the Productivity of Composite Maize Varieties in Gorontalo

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ABSTRACT
The challenge of composite maize developing in the future is the low productivity because the maize is grown on land that is not suitable for land quality. This study aims to determine the land quality and land characteristics that control the composite maize productivity in Gorontalo Province. A total of 33 land units were surveyed and their land observed to obtain data on morphology and soil characteristics, climate and terrain characteristics, as well as composite maize productivity data through ubinan plots and direct interviews with maize farmers. Partial least square of structural equation models (PLS-SEM) analysis has been used to determine the land quality and land characteristics that control the composite maize productivity through variable validity and reliability tests, as well as structural model tests. The results showed that the manifest variables were air temperature, rainfall, wet months, dry months, LGP, drainage, coarse materials, effective depth, pH H_2O, pH KCl, C-organic, total N, available P, available K, ESP, slopes, soil erosion, inundation height, inundation time, surface rock, and rock outcrops were valid and able to explain well the latent variables. Furthermore, the latent variables were temperature, water availability, oxygen availability, nutrient retention, nutrients availability, sodicity, erosion hazard, flood hazard, and land preparation used has good composite reliability and high reliability because of the composite reliability and alpha cronbach >0.6. Land quality that controls the composite maize productivity based on the order of importance were nutrient retention, rooting media, land preparation, and nutrients availability. Meanwhile, land characteristics that control the composite maize productivity based on the order of importance were pH KCI, coarse material, rock outcrops, effective depth, surface rock, available K, and soil texture. Soil texture, effective depth, pH KCI, and available K has a positive relationship and has a significant to very significant effect on the composite maize productivity, while the content of course materials, surface rock, and rock outcrops has a negative relationship and has a significant effect on the composite maize productivity.

Keywords: Quality, characteristic, land, productivity, maize, composite.

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INTRODUCTION
Low maize productivity is still a major problem in efforts to increase maize production in Indonesia. Until 2018, maize productivity had only reached 5.24 tons/ha [1], while the potential for maize productivity in Indonesia could reach 10-11 tons/ha [2]. Even though the government has rolled out various programs to increase maize production and productivity in order to achieve national maize self-sufficiency.

Gorontalo Province is one of the maizes producing centers in Indonesia with an average maize productivity achievement until 2019 of 5.03 tons/ha [3] or still far below the average national maize productivity. All this time, maize farmers has been more dominant in planting maize with hybrid and composite varieties. There are no references to the productivity of hybrid or composite maize in this area, so it is assumed that the maize productivity achievements are relatively the same at 5.24 tons/ ha. In fact, specifically the productivity of composite maize can reach 5-6 tons/ha [4] [5] or as much as 8.5 tons/ha [6]. Composite maize, besides its production potential is relatively similar to that of hybrid maize, it also has advantages, including being more adaptive in acid soils [5] and can be used as seeds for the next growing season, while hybrid maize can't be planted again. The use of composite maize can reduce the dependence of maize farmers on hybrid maize seed assistance from the government, so that if the maize seed subsidy is stopped, the farmers can plant the composite maize again.

The challenge ahead in developing composite maize is the low productivity of composite maize, so it is necessary to address the root of the problem. Maize planted on land with low productivity potential is one of the causes for the low productivity of maize [7]. Meanwhile, land characteristics and quality have a close relationship with maize productivity [8] and each land quality has a significant effect on land suitability for certain uses [9], especially for maize. Research on land quality that controls the productivity of composite maize has been conducted in the Bogor area using stepwise regression analysis [10]. The use of structural equation modeling (SEM) analysis in determining the characteristics and quality of land that control plant productivity has not been widely published, except for [11] who used SEM analysis on older cocoa plants in Kolaka Timur Regency, Southeast Sulawesi Province. Meanwhile, the use of SEM analysis specifically to determine the relationship between land quality and maize productivity has not been found.

The response of maize plants to the diversity of characteristics and quality of land will vary, so it is important to know the quality and characteristics of the land that control the productivity of maize. The diversity of characteristics and complex quality of land in the field really requires a comprehensive analysis technique that is able to simplify the complexity in one analysis system. One analysis option is to use SEM analysis. SEM analysis is able to analyze how much influence each indicator (manifest) of soil physical and chemical properties (latent) has on production in one analysis unit [11]. The use of SEM is very helpful to determine the effect on indicators and to produce a model that is better than other multivariate analyzes [12] [13]. Partial Least Square (PLS) is a variant of SEM which has a higher level of flexibility because PLS is based on variants, so that the number of samples used does not need to be large, ranges from 30-100, and does not require normal multivariate assumptions compared to CB-SEM. requires a large data sample size (> 100) and the data must be multivariate normal distribution [14] [15]. Therefore, a research on land quality that controls the productivity of composite maize was carried out using SEM-PLS analysis based on the consideration of complex land characteristics and quality, as well as limited data in the land unit in the study area. The purpose of this study was to determine the quality and characteristics of land that control the productivity of composite maize in Gorontalo.

MATERIALS AND METHOD

This research is located in the Sustainable Agriculture Area of Gorontalo Province (Figure 1) and the Soil Laboratory of the Department of Soil, Faculty of Agriculture, Brawijaya University. The timing of this research was started in December 2019 - May 2020. The tools used included the computer, SmatPLS version 2.0, SPSS, Microsoft Excel, and Microsoft Word. While the materials studied included the morphological data and soil characteristics, climate and terrain characteristics data that had been grouped into their respective land qualities, as well as composite maize productivity data from the study area.

Soil surveys and land observations were carried out to obtain morphological data and soil characteristics, climate and terrain characteristics data from the research area. Meanwhile, composite maize productivity data was obtained from the results of ubinan directly on the land of maize farmers and from direct interviews with maize farmers on 33 land units. Furthermore, the diversity of sizes and data units (ratio data) of land characteristics were converted in the form of interval data which were represented as follows were 1 (very low), 2 (low), 3 (medium), 4 (high), and 5 (very high)). After the data is ready, the analysis process is continued using SEM-PLS (Figure 2).

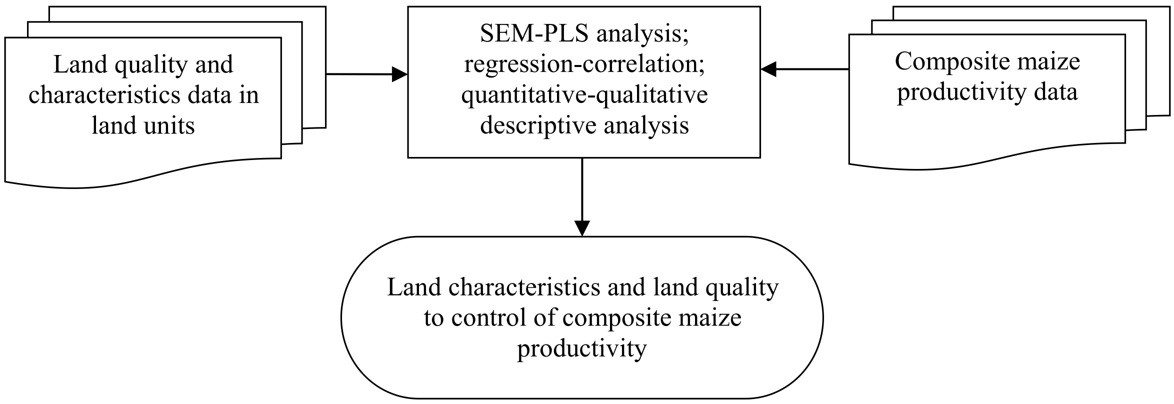

Figure 2. Research Operational Framework

The latent variable in this study was the quality of the land consisting of: temperature (X1), water availability (X2), oxygen availability (X3), root media (X4), nutrient retention (X5), available nutrients (X6), sodicity (X7), erosion hazard (X8), flood hazard (X9), and land preparation (X10). While the manifest variable was the characteristic of the land which consists of temperature (X1.1), rainfall (X2.1), wet months (X2.2), dry months (X2.3), LGP (X2.4), drainage. (X3.1), texture (X4.1), coarse material (X4.2), effective soil depth (X4.3), pH H2O (X5.1), pH KCI (X5.2), C-organic (X5.3), CEC (X5.4), base saturation (X5.5), total N (X6.1), available P2O5 (X6.2), K available (X6.3), ESP (X7.1), slope (X8.1), soil erosion (X8.2), inundation height (X9.1), length of inundation (X9.2), surface rock (X10.1), and rock outcrop (X10.2). The use of SEM-PLS in this study consisted of testing the validity, reliability of the research variables, and testing the structural model. In summary, the test using SEM-PLS was described as follows:

a. Testing the Validity of Research Variables. The basic evaluation carried out in the SEM-PLS analysis is to evaluate the measurement model (outer model) with the aim of knowing the validity and reliability of indicators in measuring research latent variables through convergent validity, discriminant validity, and composite reliability. Convergent validity testing on SEM-PLS is seen from the size of the outer loading of each indicator on its latent variable. A loading factor value above 0.70 is highly recommended, but a loading factor value of 0.50-0.60 can still be tolerated with a t-statistic value of more than 1.96 or a small p-value of 0.05. The loading factor of an indicator with the highest value is the strongest or most important measure in reflecting the latent variable in question. Discriminant validity is an evaluation of the outer model in SEM-PLS using cross loading values to test valid and reliable indicators in explaining or reflecting latent variables. If the correlation of the latent variable with the measurement core of each indicator is greater than the other latent variables, then the latent variable is able to predict the indicator better than other latent variables and is said to be valid.
b. Research Variable Reliability Testing. Composite reliability and alpha cronbach were used to test the reliability value between the indicators of the latent variables that formed them. The composite reliability value and Cronbach's alpha are said to be good, if the value is> 0.60.
c. Structural Model Testing. Testing of the structural model (inner model) is carried out after the relationship model is built in accordance with the observed data and the suitability of the overall model (goodness of fit model). Testing of structural models and hypotheses is carried out by looking at the estimated value of the path coefficient and the critical point value (t-statistic) which is significant at $\alpha = 0.05$.

Testing the relationship model and hypothesis between variables can be done by testing the direct correlation coefficient between variables. The results of testing the relationship between the X variables and the Y variable in this study are shown by the correlation coefficient and t-statistic, and also seen in the path diagram.

RESULTS AND DISCUSSION

a. Research Variable Validity

The loading factor value of the research variables, where the loading factor value on the indicators was mostly more than the critical limit of 0.7 with a confidence level of 95% (Table 1). The value of the loading factor which is below the tolerance value of 0.5 at the 95% confidence level where the t-statistic value of each indicator is smaller than the t-table (1,960) is found in the soil texture indicator of the latent variable root media (X_4) which is only 0.173 is also the CEC indicator ($X_{5.4}$) and the base saturation indicator ($X_{5.5}$) of the nutrient retention latent variable (X_5), which are only 0.399 and 0.482 respectively. This means that these indicators have not been able to properly form or explain their latent variables.

Table 1. Outer loading research variables

Effect of indicators on latent variables			Loading factors	Status
Air temperature ($X_{1.1}$)	->	Temperature (X_1)	1.000	Valid
Rainfall ($X_{2.1}$)	->	Water availability (X_2)	0.981	Valid
Wet months ($X_{2.2}$)	->		0.989	Valid
Dry months ($X_{2.3}$)	->		0.827	Valid
LGP ($X_{2.4}$)	->		0.968	Valid
Drainage ($X_{3.1}$)	->	Oxygen availability (X_3)	1.000	Valid
Texture ($X_{4.1}$)	->	Rooting media (X_4)	**0.173**	**Not valid**
Coarse material ($X_{4.2}$)	->		-0.921	Valid
Effective depth ($X_{4.3}$)	->		0.912	Valid
pH H_2O ($X_{5.1}$)	->	Nutrient retention (X_5)	0.768	Valid
pH KCI ($X_{5.2}$)	->		0.772	Valid
C-Organic ($X_{5.3}$)	->		0.710	Valid
CEC ($X_{5.4}$)	->		**0.399**	**Not valid**
Base saturation ($X_{5.5}$)	->		**0.482**	**Not valid**
N Total ($X_{6.1}$)	->	Nutrient availability (X_6)	0.799	Valid
Available P ($X_{6.2}$)	->		0.521	Valid
Available K ($X_{6.3}$)	->		0.886	Valid
ESP ($X_{7.1}$)	->	Sodicity (X_7)	1.000	Valid
Slope ($X_{8.1}$)	->	Erosion hazard (X_8)	0.974	Valid
Soil erosion ($X_{8.2}$)	->		0.957	Valid
Inundation height ($X_{9.1}$)	->	Flooding hazard (X_9)	0.993	Valid
Inundation period ($X_{9.2}$)	->		0.991	Valid
Surface rock ($X_{10.1}$)	->	Land preparation (X_{10})	0.998	Valid
Rock outcrop ($X_{10.2}$)	->		0.998	Valid
Productivity ($Y_{1.1}$)	->	Local maize productivity (Y_1)	1.000	Valid

Table 2. Cross loading of research variables

Indikator	Temperature (X_1)	Water availability (X_2)	Oxygen availability (X_3)	Rooting media (X_4)	Nutrient retention (X_5)	Nutrient availability (X_6)	Sodicity (X_7)	Erosion hazard (X_8)	Flooding hazard (X_9)	Land preparation (X_{10})	Composite maize productivity (Y_1)
Air temperature ($X_{1.1}$)	1	0.952309	0.059098	-0.08736	-0.37805	-0.06653	0.38176	0.016269	-0.10297	0.19833	0.042282
Rainfall ($X_{2.1}$)	0.968555	0.980906	0.114576	0.052348	-0.24379	0.058536	0.356547	-0.0379	-0.04621	0.056015	0.156751
Wet months ($X_{2.2}$)	0.926635	0.989185	0.173659	-0.005903	-0.25644	0.062873	0.374745	-0.06373	-0.04367	0.060342	0.177251
Dry months ($X_{2.3}$)	0.759123	0.82697	0.141078	-0.238735	-0.42612	-0.10563	0.47553	-0.11715	0.027746	0.215367	0.076041
LGP ($X_{2.4}$)	0.900431	0.96821	0.13569	-0.003834	-0.28223	0.056251	0.459669	-0.12209	-0.04398	0.059938	0.193991
Drainage ($X_{3.1}$)	0.059098	0.144225	1	0.129338	-0.24128	0.057861	0.084339	-0.50344	0.236555	-0.22277	0.400657
Texture ($X_{4.1}$)	-0.02057	-0.01261	-0.16957	**0.172551**	0.242032	0.12283	0.217308	0.196875	-0.00074	-0.02261	0.09248
Coarse material ($X_{4.2}$)	-0.00333	-0.1005	-0.13244	-0.921096	-0.38256	-0.6112	0.18822	0.322934	-0.26391	0.846957	-0.35202
Effective depth ($X_{4.3}$)	-0.17758	-0.09256	0.165016	0.912088	0.3519	0.355112	-0.23141	-0.19005	0.095721	-0.76736	0.180089
pH H_2O ($X_{5.1}$)	-0.40346	-0.38437	-0.3719	0.29356	0.767791	0.27088	-0.17175	0.151553	-0.02966	-0.08478	0.186569
pH KCl ($X_{5.2}$)	-0.25953	-0.22811	-0.44804	0.342269	0.771872	0.272936	-0.02729	0.167533	0.098977	-0.18312	0.268161
C-Organic ($X_{5.3}$)	-0.29516	-0.13852	0.096529	0.248076	0.710022	0.612498	0.073184	-0.4692	0.063874	-0.1793	0.384332
CEC ($X_{5.4}$)	0.066756	0.115697	0.003345	0.084182	**0.399393**	0.421251	0.373179	-0.05735	0.15285	-0.01387	0.281455
Base saturation ($X_{5.5}$)	-0.30026	-0.25724	-0.10527	0.412102	**0.481624**	0.361795	-0.60079	-0.0895	-0.13592	-0.48759	0.136266
N Total ($X_{6.1}$)	0.002878	0.137879	0.07154	0.268606	0.545283	0.798694	0.030267	-0.37884	-0.10212	-0.2485	0.427705
Available P ($X_{6.2}$)	-0.09821	-0.09791	-0.44547	0.211821	0.409315	0.520984	-0.28705	-0.057	0.033581	-0.26033	-0.02547
Available K($X_{6.3}$)	-0.09732	-0.01031	0.06693	0.614343	0.51245	0.885686	-0.3292	-0.29441	0.237691	-0.6422	0.49531
ESP ($X_{7.1}$)	0.38176	0.405078	0.084339	-0.186069	-0.06947	-0.21259	1	-0.01035	0.201152	0.361936	-0.0249
Slope ($X_{8.1}$)	-0.02207	-0.12714	-0.51717	-0.295103	-0.1643	-0.40295	-0.03466	0.973779	-0.34215	0.324431	-0.64795
Soil erosion ($X_{8.2}$)	0.064136	-0.00224	-0.44709	-0.166166	-0.11161	-0.32907	0.021581	0.956588	-0.12926	0.257787	-0.48649
Inundation height ($X_{9.1}$)	-0.08956	-0.02635	0.225421	0.194354	0.082178	0.127762	0.193925	-0.26735	0.992798	-0.13415	0.175472
Inundation period ($X_{9.2}$)	-0.11594	-0.06329	0.244833	0.199427	0.048584	0.078386	0.205739	-0.2425	0.991369	-0.11616	0.135302
Surface rock ($X_{10.1}$)	0.212772	0.074279	-0.23401	-0.854273	-0.28568	-0.55023	0.376036	0.319248	-0.13208	0.997623	-0.28655
Rock outcrop ($X_{10.2}$)	0.183196	0.051703	-0.21067	-0.868319	-0.29655	-0.55537	0.34638	0.290608	-0.12053	0.997697	-0.28228
Productivity ($Y_{1.1}$)	0.042282	0.177277	0.400657	0.304774	0.418519	0.534535	-0.0249	-0.59733	0.157534	-0.28507	1

The standard of loading factor is greater equal to 0.50 [16] [17] [13]. However, in general, based on the indicated values, it can be concluded that the latent variables of land quality have been able to be well established or explained by each indicator and can be said to be convergent valid on these indicators. The cross-loading value for the indicators of latent variables on average is above the cross-loading value of the indicators for other latent variables (Table 2). That is, the greatest cross loading value on the indicator is found in the latent variable too, except for the texture indicator ($X_{4.1}$) of the root media variable (X_4), the CEC indicator ($X_{5.4}$) and base saturation ($X_{5.5}$) of the nutrient retention variable (X_5) whose cross loading value is still smaller (<0.5) than the cross loading value of other latent variables. The standard of loading factor is ≥0.50 [16] [17] [13]. Thus, the indicators of each latent variable are mostly able to explain the latent variable itself better than the other variables, so that the research variables are said to be discriminant valid.

b. Reliability of Research Variables

Composite reliability and Cronbach alpha were used to test the reliability value between the indicators of the latent variables that formed them. The composite reliability value and Cronbach's alpha are said to be good, if the value is above 0.60 [18]. The composite reliability value on each research variable is more than the limit value (>0.6), except for the root media variable (Table 3). The composite reliability value and the Cronbach alpha value is greater than 0.6 so that the latent variable has good composite reliability and high reliability. A construct is said to be reliable if the Cronbach Alpha value must be >0.6 [19]. Thus, all indicators used in this study have met the criteria or are feasible to be used in the measurement of all latent variables because they have good validity and high reliability. The results of the evaluation of convergent validity and discriminant validity of indicators or variables as well as composite reliability and alpha Cronbach for indicators or variables can be concluded that the indicators as measures of latent variables are valid and reliable measures respectively.

Table 3. Composite reliability and Cronbach's Alpha values of research variables

Laten variables	Composite reliability	*Alpha Cronbach*
Temperature (X_1)	1.000000	1.000000
Water availability (X_2)	0.970030	0.965126
Oxygen availability (X_3)	1.000000	1.000000
Rooting media (X_4)	**0.020314**	**-1.055192**
Nutrient retention (X_5)	0.770518	0.628062
Nutrient availability (X_6)	0.788289	0.681393
Sodicity (X_7)	1.000000	1.000000
Erosion hazard (X_8)	0.964615	0.927731
Flooding hazard (X_9)	0.992053	0.984010
Land preparation (X_{10})	0.997657	0.995304

b. Structural Model Testing

The structural model (inner model) is evaluated by looking at the coefficient value of the relationship path parameter between latent variables. It seems that the soil quality of the root media, nutrient retention, and available nutrients showed a positive correlation and had a significant effect on the productivity of composite maize (Table 4). The quality of land preparation shows a negative correlation and has a significant effect on the productivity of composite maize. This indicates that the better rooting media, available nutrient and nutrient retention and a decrease in the level of land preparation as the productivity of composite maize increases. The results of this study are slightly different from the research report [8] regarding the quality of soil rooting media which has not affected the productivity of maize in the Bogor area, but the quality of soil nutrient retention and available nutrients has a significant effect on the productivity of maize relatively the same as the results of this study.

Table 4. Path coefficient and significance testing

Exogenous variables	Composite maize produktivity (Y)	
	Path coeffisient	t-statistics ($t_{critics}$ = 2.00)
Temperature (X_1)	0.086	1.531
Water availability (X_2)	0.457	-0.491
Oxygen availability (X_3)	0.099	0.371
Rooting media (X_4)	**0.091***	2.250
Nutrient retention (X_5)	**0.740***	2.291
Nutrient availability (X_6)	**0.283****	6.509
Sodicity (X_7)	-0.194	-0.036
Erosion hazard (X_8)	-0.043	-1.043
Flooding hazard (X_9)	0.050	-0.050
Land preparation (X_{10})	**-0.386***	-2.339

Significant on level test of 5%; ** Significant on level test of 1%

c. Land quality and characteristics that controlling of composite maize productivity

Based on the previous structural model testing, the most influential land quality and control of composite maize productivity based on the order of importance were nutrient retention, root media, land preparation, and available nutrients. This was also based on the results of multiple regression tests with the best equation (equation 1) of the land quality that affects composite maize production were:

$Y = 5.892 + 0.430X_1 + 0.453X_2 + 0.248X_3 - 0.443X_4$ ……………………………… (1)

r = 0.56

Where: X_1 = root medium, X_2 = nutrient retention, X_3 = nutrients availability, X_4 = land preparation. Furthermore, the land characteristics that most influenced the productivity of composite maize based on the order of importance were pH KCI, coarse material, rock outcrop, effective depth, surface rock, available K, and soil texture. This was also based on the results of multiple regression tests with the best equation (equation 2) as follows:

$Y = 4.531 + 0.450X_1 - 0.351X_2 - 0.365X_3 + 0.321X_4 - 0.352X_5 + 0.351X_6 + 0.337X_1$... (2)

r = 0.63

Where: X_1 = pH of KCl, X_2 = coarse material, X_3 = rock outcrop, X_4 = effective depth, X_5 = surface rock, X_6 = K available, X_7 = soil texture.

The relationship of each land characteristic and its contribution to land quality in influencing the composite maize productivity was presented in Table 5 and Figure 3. The land characteristics consisting of texture, effective depth, pH of KCI, and available K has a positive relationship and significant effect on the composite maize productivity. This shows that the increasing of the land characteristics by 1%, the composite maize productivity will increase by 30% to 47%. In contrast, the content of coarse material, surface rock, and rock outcrops has a negative relationship and significant effect on the composite maize productivity. This indicates that the decreasing content of coarse material, surface rock, and rock outcrops was 1% each in line with the increase in the composite maize productivity by 42% to 44%. The correlation of each of these land characteristics was quite strong in influencing the composite maize productivity. Coarse material is rock fragments measuring 2 mm in diameter or more which affect soil moisture, infiltration, erosion, and land use [20]. Coarse material <15% is very suitable for maize, while > 55% is not suitable [21] [22] [23]. The most suitable soil texture for maize is a fine or loamy texture [24]. Meanwhile, the deeper effective depth affects root growth and development, so that plants can grow and develop well [25]. Surface rocks and rock outcrops are limiting factors in the suitability of maize land in Saentis Village [26].

Table 5. Coefficient of correlation and contribution level on land quality of the land characteristics and composite maize productivity

Coefficient of correlation	Contribution on land quality (%)	Coefficient of correlation
Temperature ($X_{1.1}$)	0.127	0.20
Rainfall ($X_{2.1}$)	0.279	17.2
Wet months ($X_{2.2}$)	0.209	13.7
Dry months ($X_{2.3}$)	-0.124	-13.2
LGP ($X_{2.4}$)	0.166	12.2
Drainage ($X_{3.1}$)	0.084	14.1
Texture ($X_{4.1}$)	**0.298***	**18.4**
Coarse material ($X_{4.2}$)	**-0.438****	**-89.4**
Effective depth ($X_{4.3}$)	**0.431****	**76.1**
pH H_2O ($X_{5.1}$)	0.254	32.0
pH KCl ($X_{5.2}$)	**0.471****	**43.2**
C-Organic ($X_{5.3}$)	0.264	41.5
CEC ($X_{5.4}$)	0.123	24.7
Base saturation ($X_{5.5}$)	0.216	47.3
N Total ($X_{6.1}$)	0.158	46.7
Available P ($X_{6.2}$)	0.012	33.2
Available K ($X_{6.3}$)	**0.368***	**77.5**
ESP ($X_{7.1}$)	-0.024	-17.1
Slope ($X_{8.1}$)	-0.266	-44.4
Soil erosion ($X_{8.2}$)	-0.158	-28.3
Inundation height ($X_{9.1}$)	0.014	23.1
Inundation period ($X_{9.2}$)	0.010	20.1
Surface rock ($X_{10.1}$)	**-0.418****	**-83.7**
Rock outcrop ($X_{10.2}$)	**-0.436****	**-85.0**

*Significant on level test of 5%; ** Significant on level test of 1%.

CONCLUSION

Land quality that controls the productivity of composite maize based on the order of importance is nutrient retention, root media, land preparation, and available nutrients. Meanwhile, land characteristics that control the productivity of composite maize based on the order of importance are pH of KCI, coarse material, rock outcrop, effective depth, surface rock, available K, and soil texture. Soil texture, effective depth, pH of KCI, and available K had a positive and significant effect on the productivity of composite maize, while the content of coarse material, surface rock, and rock outcrops had a negative relationship and had a significant effect on the productivity of composite maize.

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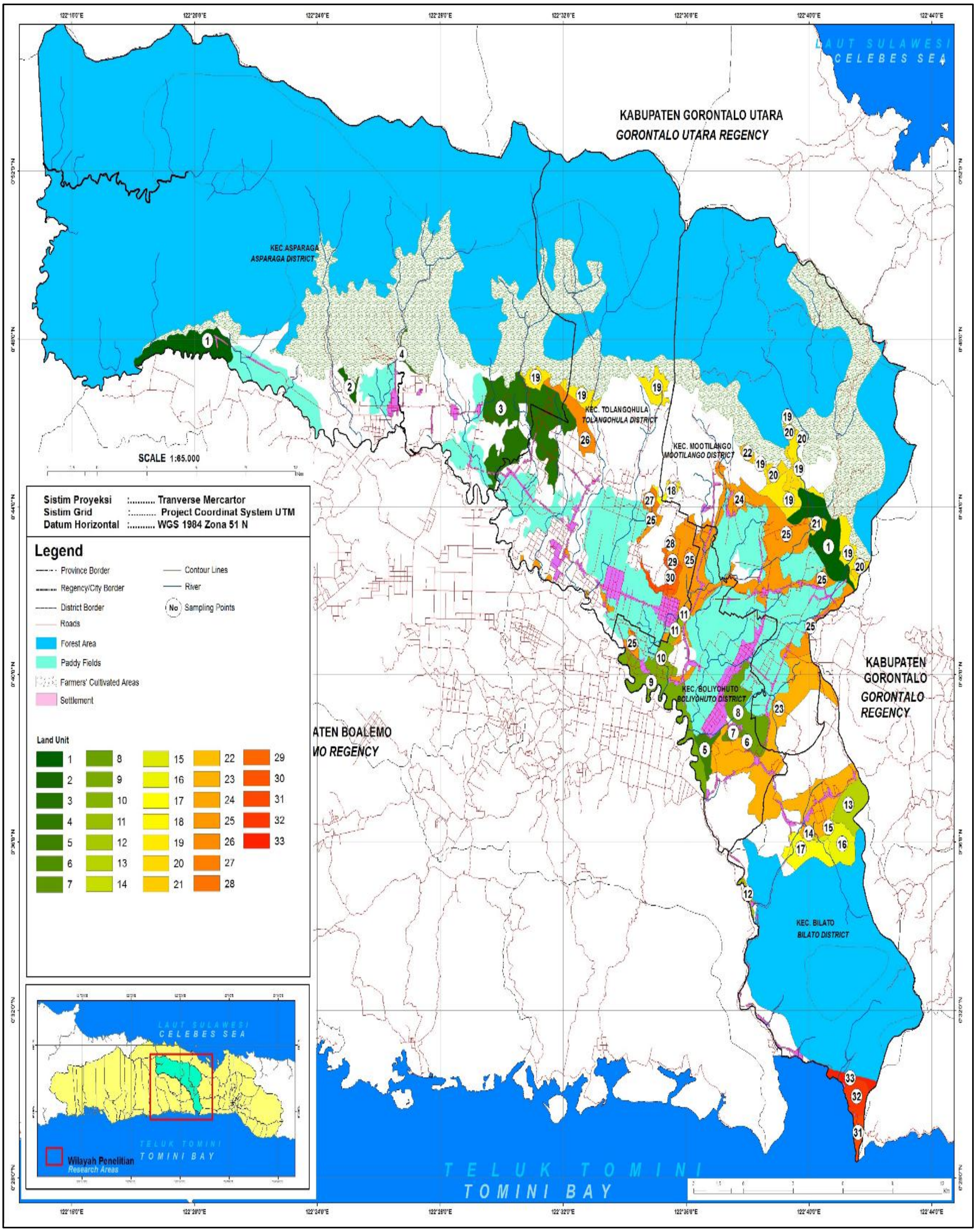

Figure 1. Map of the Research Location

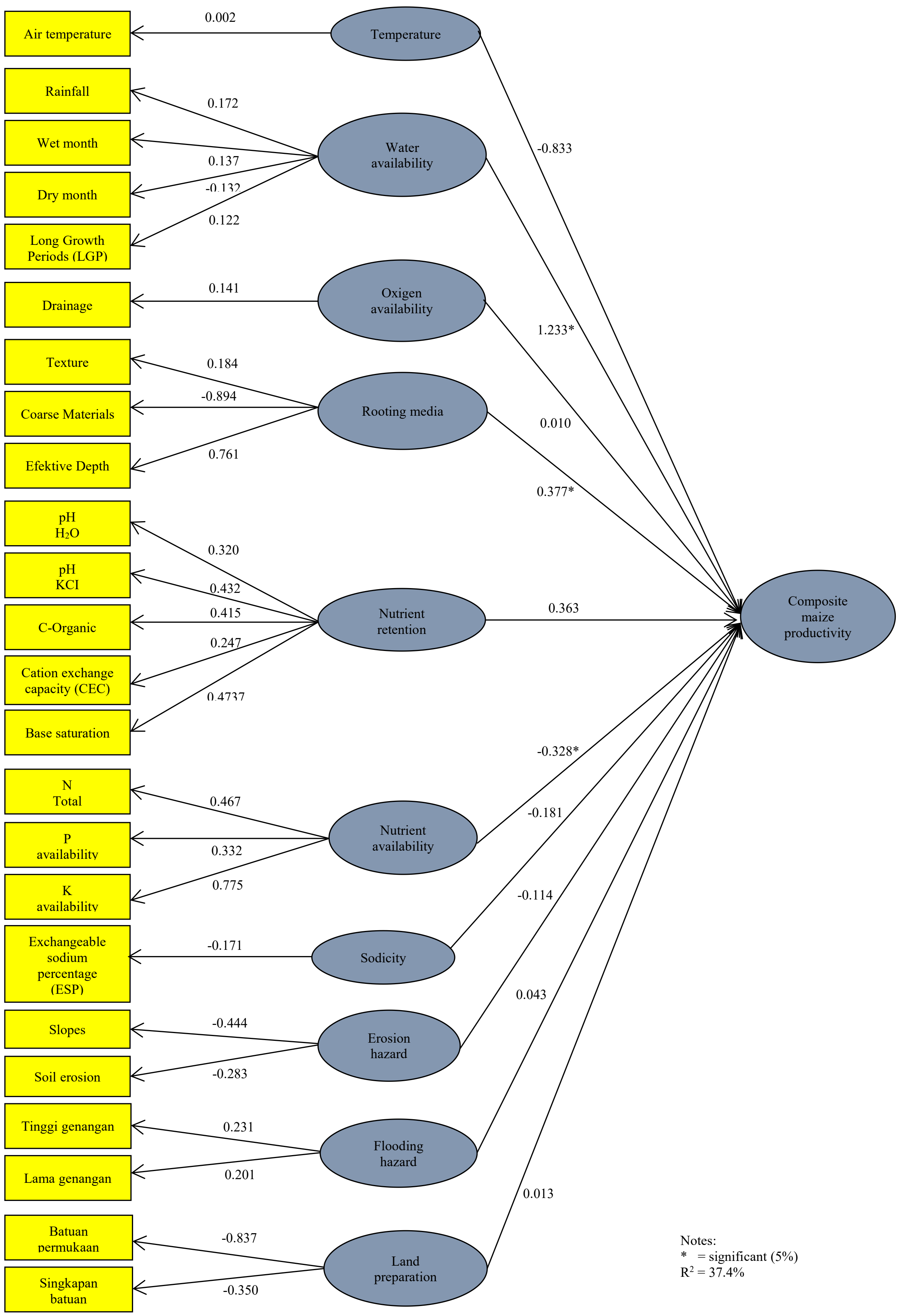
Air temperature
0.002
Temperature
Rainfall
Wet month
Dry month
Long Growth Periods (LGP)
0.172
0.137
-0.132
0.122
Water availability
-0.833
Drainage
0.141
Oxigen availability
1.233*
Texture
Coarse Materials
Efektive Depth
0.184
-0.894
0.761
Rooting media
0.010
0.377*
pH H2O
pH KCI
C-Organic
Cation exchange capacity (CEC)
Base saturation
0.320
0.432
0.415
0.247
0.4737
Nutrient retention
0.363
Composite maize productivity
N Total
P availability
K availability
0.467
0.332
0.775
Nutrient availability
-0.328*
-0.181
Exchangeable sodium percentage (ESP)
-0.171
Sodicity
-0.114
Slopes
Soil erosion
-0.444
-0.283
Erosion hazard
0.043
Tinggi genangan
Lama genangan
0.231
0.201
Flooding hazard
0.013
Batuan permukaan
Singkapan batuan
-0.837
-0.350
Land preparation
Notes:
* = significant (5%)
R2 = 37.4%

Figure 3. Path coefficient diagram of land quality to productivity level of composite maize