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SUPPORT VECTOR REGRESSION (SVR) METHOD FOR PADDY GROWTH PHASE MODELING USING SENTINEL-1 IMAGE DATA

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Abstract: Support Vector Machines (SVMs) is a kernel-based ML method that has received extensive attention over the last decade because it is claimed to be able to produce accurate models that have good predictions in various situations and can accommodate linear combinations of explanatory variables. This study aims to test the SVR method for modeling the growth phase of paddy using sentinel-1 image data. This method was compared for its accuracy with the LR method using RMSE and R^2 statistics and model stability using 10 repetitions. The accuracy of the model with the two best predictors is when the NDPI and API Polarization Index are the predictors. The paddy age model from the SVR method is better than the paddy age model from the LR method, where the SVR method produces a model with an average RMSE of 11.13 and an average coefficient of determination of 88.10%. The accuracy of the SVR model with NDPI and API predictors can be improved by adding VH polarization to the model, where the average RMSE statistic decreases to 11.0 and the average coefficient of determination becomes 88.42%. In this scenario, the best model gives a minimum RMSE value of 10.35 and a coefficient of determination of 90.05%.

1. INTRODUCTION

In the last decade, Machine learning (ML) methods have received extensive attention because they can find data patterns automatically and can increase efficiency and reduce costs in the computing process (Rahmani et al., 2021). Support Vector Machines (SVMs) are kernel-based ML methods that can be used for classification and regression. This method has also received extensive attention over the last decade because it is claimed to be able to produce accurate models, have good predictions in various situations, and can accommodate linear combinations of explanatory variables (Clark, 2013). The SVM method was implemented by (Guo & Chou, 2020) for the analysis of cancer models, for the prediction of wind energy by (Ahmadi & Khashei, 2021), and prediction of paddy planting areas using remote sensing data by Gandharum *et al.* (2021).

In many real-world applications, the relationships between variables are nonlinear. The use of the kernel makes the SVR method capable of considering complex non-linear relationships between variables (Moqaddasi Amiri et al., 2019). Non-linear relationships can be solved with slack variables and kernel tricks. Kernel tricks are the main features of SVM which can map problems to a higher dimensional space so that non-linear relationships become quite linear(Gaurav & Patel, 2020).

Paddy is the main food commodity for Indonesia, so it requires comprehensive management from the aspect of land management and post-harvest. The use of optical satellite data such as MODIS, Landsat, and Sentinel-2 for modeling paddy phases in several parts of the world using machine learning methods has been able to produce a model accuracy of more than 85%(Zhao et al., 2021). However, the use of optical satellite data in Indonesia is not optimal because the area of Indonesia which is in a tropical climate has high rainfall and thick fog, and cloud coverage often causes the appearance of objects in optical imagery to be often obscured by clouds. The solution is to use a satellite data radar such as Sentinel-1 because it can be used in almost any weather condition (Sutanto et al., 2014).

The use of radar satellite data such as Sentinel-1 for modeling paddy phases using machine learning methods in several parts of the world has also resulted in very good accuracy. (Zhao et al., 2021). In Indonesia, the research of (Gandharum et al., 2021) using the Sentinel-1 radar satellite-based SVM method in Indramayu was able to produce a paddy planting area model with an accuracy of up to 81.89%. However, this study only used the VH polarization, whereas, in the Sentinel-1 satellite data, 3 polarizations were available, namely VV, VH, and VV-VH and their derivatives, such as RPI, NDPI, and API. Research of (Dirgahayu & Made Parsa, 2019) using the RPI polarization index to model the paddy growth phase using the linear regression (LR) method. The results showed that RPI can describe the phenomenology of paddy growth. However, the LR method for time series data has the potential to experience autocorrelation problems (Triscowati et al., 2019). In addition, ideally, the LR model must also meet the assumptions of residual normality, be free of multicollinearity and heteroscedasticity and not be strong in facing outlier problems. (Gaurav & Patel, 2020).

Based on the explanation above, it can be seen that the paddy growth phase model, especially in Indonesia, relies more on the LR model. Unfortunately, the LR method is prone to assumption violations and is not robust with outlier problems. One solution is to use ML methods that are not plagued with model assumption problems and outlier problems(Gaurav & Patel, 2020). In this study, we apply the SVR method to model the age of paddy using Sentinel-1 data. The accuracy and stability of the SVR model are compared with the LR method. The results of this study are expected to be a solution to the age/phase model of paddy in Indonesia which can produce information even in cloud conditions.

2. LITERATURE REVIEW

The general matrix form of the linear model is as follows (Stroup, 2013);

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e} \quad (1)$$

Where $\mathbf{y}$ is the response variable vector, $\mathbf{X}$ is the estimating variable matrix, $\boldsymbol{\beta}$ is the regression coefficient vector with p-dimensional, and e is the error vector which is assumed to be normally distributed.

If there is only one explanatory variable, it is called simple regression and if there is more than one explanatory variable, it is called multiple regression (Faraway, 2004). Equation (1) can be expressed in the form (Ostertagová, 2012);

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + e_i, for\ i = 1,2,\ldots,n \quad (2)$$

Estimating the parameter $\boldsymbol{\beta}$ using the least squares method yields the following results (Ostertagová, 2012):

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathbf{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{y} \quad (3)$$

A special form of multiple regression is polynomial regression where there is only one independent variable that can be expressed in the equation;

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \cdots + \beta_p x_i^p + e_i, for\ i = 1,2, \ldots, n \quad (4)$$

Kernel functions are functions $\kappa(\mathbf{x}, \mathbf{x}') \in R$ which can be a measure of similarity/distance between objects. The kernel function is non-negative, namely $\kappa(\mathbf{x}, \mathbf{x}') \geq 0$ and symmetric, namely $\kappa(\mathbf{x}, \mathbf{x}') = \kappa(\mathbf{x}', \mathbf{x})$Kernel functions consist of various forms, for example, linear kernel, polynomial kernel, and radial basis function (RBF). (Murphy, 2012). The kernel function becomes a solution when the relationship between variables is not linear.

Table 1. The Kernel Types

Type Kernel	Equation
RBF Kernel	$\kappa(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{\lVert\mathbf{x} - \boldsymbol{x}'\rVert^2}{2\sigma^2}\right)$ σ^2 is called the bandwidth
Polynomial Kernel	$\kappa(\mathbf{x}, \mathbf{x}') = (\mathbf{x}^T\mathbf{x}' + r)^M$ $r > 0$ M is the degree of the polynomial
Linear Kernel	$\kappa(\mathbf{x}, \mathbf{x}') = \mathbf{x}^T\mathbf{x}'$

The goal of SVM is to create a flat boundary, called a hyperplane which is a linear boundary for partitioning data into homogeneous groups. All hyperplanes in $\boldsymbol{R^d}$ are parameterized by a vector ($\mathbf{w}$) which is orthogonal to the hyperplane, and a constant ((w_0) which is the bias. The hyperplane equation is expressed in the equation (Caraka et al., 2020; Schölkop, 2003):

$$\mathbf{w}^T\mathbf{x}_i + w_0 = 0 \quad (5)$$

The support Vector is the closest point to the maximum margin hyperplane (MMH). Each class has at least one support vector. Hyperlane is chosen by maximizing the margin support vector of the two classes, the maximum margin is MMH. The objective function for SVR can be written as follows:

$$J = C\sum_{i=1}^{N} L_\varepsilon(y_i, \hat{y}_i) + \frac{1}{2}\lVert\mathbf{w}\rVert^2 \quad (6)$$

Where $L_\varepsilon(y_i, \hat{y}_i)$ is an epsilon insensitive loss function that can be written as:

$$L_\varepsilon(y_i, \hat{y}_i) \triangleq \begin{cases} 0 \text{ if } |y - \hat{y}| < \varepsilon \\ |y - \hat{y}| - \varepsilon\ else \end{cases} \quad (7)$$

$\hat{y}_i = f(\mathbf{x_i}) = \mathbf{w^T x_i} + w_0$ and $C = \frac{1}{\lambda}$ constant.

The objective function J is convex and unconstrained but not differentiable because $L_\varepsilon(y_i, \hat{y}_i) = 0$ for $|y - \hat{y}| < \varepsilon$. One popular approach is to formulate this problem as a constrained optimization problem by using the slack variable (ξ) which represents how far each point lies outside the tube. The objective function becomes a quadratic function of w with the following equation;

$$J = C\sum_{i=1}^{N}(\xi_i^+ + \xi_i^-) + \frac{1}{2}\lVert\mathbf{w}\rVert^2 \quad (8)$$

With constraints;

$$\boldsymbol{y}_i \leq f(\mathbf{x_i}) + \epsilon + \xi_i^+, \xi_i^+ \geq 0$$
$$\boldsymbol{y}_i \geq f(\mathbf{x_i}) - \epsilon - i, \xi_i^- \geq 0$$

To get a solution of an objective function and a set of constraints, you can use the Lagrange Multiplier method. This method is an alternative method for non-linear optimization problems with constraints in the form of equations or inequalities. On the standard form of a nonlinear optimization problem with an objective function;

$$\min f(x_1, \dots, x_n)$$

With Constraint;

$$\mathbf{G}(x_1, \dots, x_n) = 0$$

$$\mathbf{G} = [G_1(x_1, \dots, x_n) = 0, \dots, G_k(x_1, \dots, x_n) = 0]^{\boldsymbol{T}}$$

The Lagrange Multiplier equation for the objective function and constraints above is as follows;

$$F(\mathbf{X}, \lambda) = f(\mathbf{X}) - \boldsymbol{\lambda}\mathbf{G}(\mathbf{X}) \quad (9)$$

Where $\mathbf{X} = [x_1, \dots, x_n]$ is a vector variable and λ is called the Lagrange Multiplier.

The optimal solution of the objective function in equation (9) with constraints is obtained by deriving the Lagrange equation (Wen & Edelman, 2000). The Lagrange equation is derived for the estimated parameters which are called the least squares method (Luts et al., 2012). The results of the optimization process are;

$$\hat{\mathbf{w}} = \textstyle\sum_i \alpha_i \mathbf{x_i} \quad (10)$$

$$\alpha_i \geq 0$$

The vector $\mathbf{x_i}$ for every $\alpha_i > 0$ is called the support vector which is the point where the fault lies on or outside the ε-tube. Kernel solution;

$$\hat{y}(\mathbf{x}) = \hat{w}_0 + \hat{\mathbf{w}}^T\mathbf{x}$$

$$\hat{y}(\mathbf{x}) = \hat{w}_0 + \sum_i \alpha_i \mathbf{x_i^T x}$$

$$\hat{y}(\mathbf{x}) = \hat{w}_0 + \textstyle\sum_i \alpha_i \kappa(\mathbf{x}_\mathrm{i}, \mathbf{x}) \quad (11)$$

3. MATERIAL AND METHOD

This research was conducted in the paddy field area of PT. Sang Hyang Seri (SHS) Subang. The research data consisted of Sentinel-1 satellite imagery in the paddy fields of PT. SHS Subang which was accessed from 07 November 2021 to 03 May 2022 and field data which is the age profile of paddy in each paddy field block. This data is research data from the paddy phase team at the BRIN Remote Sensing Research Center.

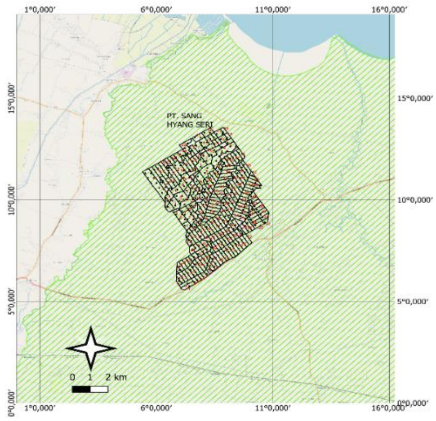

Figure 1. Research Areas

The independent variables in this study are the polarization of the Sentinel-1 satellite, the polarization index, and the growing season. Sentinel-1 satellite polarization has a measuring scale in decibel units. The polarization index, namely the Normalized Different

Polarization Index (NDPI), the Ratio Polarization Index (RPI), and the Average Polarization Index (API) are derivatives of polarization with the following formula (Dirgahayu & Made Parsa, 2019);

$$NDPI = \frac{VV - VH}{VV + VH}$$

$$RPI = \frac{VH}{VV}$$

$$API = \frac{VV + VH}{2}$$

The sample in this study was 4315 sample units. The sample data is randomly divided into 70% for training data and 30% for testing data. To see the stability of the model, we experimented by dividing the training data and testing data 10 times. The obtained model accuracy is tested using the Root Mean Square Error (RMSE) statistic(Ahmadi & Khashei, 2021) and Coefficient of Determination (R^2) (Raza et al., 2019). The SVR method is implemented using Package e1070 (Meyer et al., 2022) while for the LR method used package caret (Kuhn et al., 2022).

3. RESULTS AND DISCUSSION

Descriptively the VV polarization has an average value of 0.103 with a standard deviation of 0.036. The VH polarization has an average value of 0.024 with a standard deviation of 0.011. The range of VV polarization values is higher than the VH polarization values. The derivative of these two polarizations, namely the NDPI polarization index, is a polarization index with the largest average value of 0.645 with a standard deviation value of 0.107. The age variable has a minimum value of 1 to 123 HST (Day after Planting) with an average value of 60.51 and a standard deviation of 34.463.

Table 2. Statistics Descriptive

Variables	Minimum	Maximum	Mean	Standard Deviation
VV	0.026	0.282	0.103	0.036
VH	0.005	0.065	0.024	0.011
RPI	0.071	0.417	0.231	0.084
NDPI	0.435	0.870	0.645	0.107
API	0.018	0.202	0.070	0.025
Age	1	123	60.51	34.463

Based on the results of the scatterplot visualization (Figure 2), shows that the polarization index and polarization index are not linear to the age of the paddy. This is following the results of the SVR analysis which shows that the use of RBF kernels is better than linear, polynomial, and sigmoid kernels. The use of the RBF kernel is also done by (Luts et al., 2012; Onojeghuo et al., 2018) which shows that the SVM method is more optimal when the RBF kernel is applied. Likewise in the LR model, based on our experimental results it shows that individually using polynomial regression of degree three is better than linear regression of degrees 1 and 2.

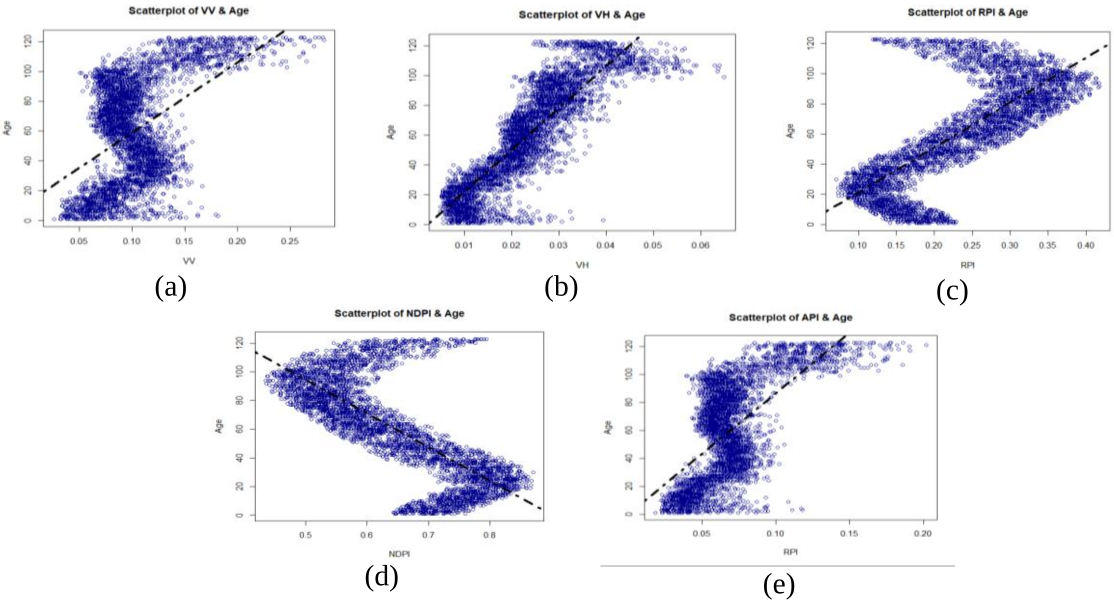

Figure 2. Scatterplot Between Polarization/Polarization Index Against Paddy Age

In the model scenario with one predictor, VH polarization provides the best model accuracy for both the SVR and LR methods. The SVR model produces an average RMSE value of 14.72 and an average value of the coefficient of determination of 77.78%. Based on the average value of these two statistics, the SVR method with the VH predictor gives better results than the LR method with the same predictor. VH polarization can describe the age of paddy with fairly good accuracy. Biophysical parameters have a stronger relationship with VH than with polarization VV (Wali et al., 2020). VH polarization is more sensitive to paddy growth and VH polarization shows a consistent increase in backscatter from plant flooding/expansion to the end of the reproductive phase (Chai et al., 2018).

SVR model accuracy increases significantly when combined with VV polarization. The average RMSE statistic decreased to 11.40 and the average coefficient of determination became 87.56%. The accuracy of the model with the two best predictors is when the NDPI and API Polarization Index are the predictors. The paddy age model from the SVR method is better than the paddy age model from the LR method, where the SVR method produces a model with an average RMSE of 11.13 and an average coefficient of determination of 88.10%. The accuracy of the SVR model with NDPI and API predictors can be improved by adding VH polarization to the model, where the average RMSE statistic decreases to 11.0 and the average coefficient of determination becomes 88.42%. In this scenario, the 7th model repetition gives a minimum RMSE value of 10.35 and a coefficient of determination of 90.05%.

Table 3. Comparison LR and SVR

Predictor	Method	RMSE				R^2			
		Min	Max	Mean	SD	Min	Max	Mean	SD
VV	LR	29.76	30.37	30.04	0.22	-260.77	-189.95	-224.6	21.23
	SVR	27.71	29.13	28.41	0.38	-58.7	-40.42	-48.08	5.48
VH	LR	14.47	15.41	14.96	0.28	75.32	78.31	76.67	0.91
	SVR	**14.13**	**15.25**	**14.72**	**0.31**	**76.43**	**79.53**	**77.78**	**0.91**
RPI	LR	22.37	23.64	22.89	0.38	16.25	22.81	20.30	2
	SVR	22.36	23.66	22.89	0.41	15.29	24.61	20.77	2.69
NDPI	LR	22.28	23.62	22.85	0.40	17.15	23.71	20.71	1.91
	SVR	22.42	23.74	22.98	0.41	15.03	24.09	20.36	2.55
API	LR	25.49	26.31	25.93	0.29	-43.31	-29.36	-32.53	5.90
	SVR	23.91	25.47	24.63	0.43	1.93	19.41	10.45	4.97
VV+VH	LR	15.78	16.40	16.06	0.22	68.69	73.73	71.75	1.44
	SVR	**10.70**	**12.06**	**11.40**	**0.38**	**86.07**	**89.35**	**87.56**	**0.88**
VV+RPI	LR	13.77	14.92	14.45	0.32	77.37	80.73	78.39	1.02
	SVR	10.66	12.09	11.46	0.41	85.73	89.30	87.20	0.99
VV+NDPI	LR	14.16	15.30	14.82	0.31	75.76	79.33	77.03	1.04
	SVR	10.68	12.10	11.48	0.40	85.74	89.23	87.16	0.98
VV+API	LR	18.16	19.30	18.76	0.35	53.36	60.66	57.91	2.56
	SVR	13.70	14.87	14.40	0.37	75.40	79.82	77.87	79.82
VH+RPI	LR	14.88	15.62	15.30	0.24	72.56	77.09	75.08	1.23
	SVR	10.71	12.25	11.66	0.44	85.41	89.10	86.71	1.08
VH+NDPI	LR	15.01	15.76	15.43	0.24	71.98	76.57	74.58	1.25
	SVR	10.67	12.19	11.61	0.43	85.57	89.19	86.84	1.04
VH+API	LR	15.99	16.64	16.27	0.21	67.89	72.82	70.72	1.43
	SVR	10.85	12.13	11.49	0.35	85.92	88.95	87.31	0.84
RPI+NDPI	LR	23.00	24.12	23.47	0.32	8.54	15.86	13.19	2.52
	SVR	22.39	23.71	22.94	0.42	14.87	24.29	20.49	2.67
RPI+API	LR	13.36	14.39	13.97	0.29	78.76	82.17	80.09	1.01
	SVR	10.47	11.75	11.16	0.35	86.67	89.72	88.00	**0.87**
NDPI+API	LR	13.71	14.74	14.30	0.29	77.46	81.01	78.96	1.05
	SVR	**10.47**	**11.69**	**11.13**	**0.34**	**86.83**	**89.74**	**88.10**	**0.84**
VV+VH+RPI	LR	13.79	14.91	14.44	0.31	77.26	80.71	78.40	1.02
	SVR	10.54	11.99	11.32	0.40	86.16	89.68	0.96	0.96
VV+VH+NDPI	LR	14.17	15.26	14.80	0.30	75.69	79.36	77.11	1.04
	SVR	10.53	11.96	11.30	0.40	86.27	89.71	87.74	0.94
VV+VH+API	LR	15.06	15.81	15.43	0.21	71.63	76.25	74.57	1.38
	SVR	10.65	11.88	11.27	0.34	86.34	89.31	87.72	0.81
VV+RPI+NDPI	LR	13.59	14.72	14.26	0.31	78.09	81.44	79.03	1.02
	SVR	10.69	12.15	11.52	0.40	85.51	89.13	87.01	0.98
VV+RPI+API	LR	13.42	14.37	13.94	0.27	78.69	82.10	80.21	1.02
	SVR	10.49	11.83	11.21	0.36	86.40	89.66	87.89	0.89
VV+NDPI+API	LR	13.75	14.68	14.24	0.27	77.47	81.01	79.20	1.06
	SVR	10.46	11.78	11.16	0.36	86.58	89.79	88.01	0.88
VH+RPI+NDPI	LR	14.50	15.22	14.93	0.23	74.36	78.62	76.48	1.16
	SVR	10.85	12.41	11.81	0.42	85.00	88.72	86.34	1.04
VH+RPI+API	LR	13.31	14.36	13.94	0.31	79.00	82.34	80.22	1.02
	SVR	10.38	11.67	11.06	0.35	86.94	89.98	88.29	0.81
VH+NDPI+API	LR	13.68	14.73	14.29	0.30	77.61	81.10	79.03	1.05
	SVR	**10.35**	**11.61**	**11.00**	**0.34**	**87.06**	**90.05**	**88.42**	**0.81**
RPI+ NDPI+ API	LR	13.15	14.14	13.76	0.30	79.66	82.92	80.77	1.01
	SVR	10.47	11.75	11.17	0.34	86.57	89.64	87.91	0.85
VV+VH+RPI+NDPI	LR	13.59	14.65	14.23	0.30	78.14	81.49	79.14	1.01
	SVR	10.54	12.00	11.35	0.40	86.06	89.58	87.52	0.95
VV+VH+RPI+API	LR	13.37	14.35	13.92	0.29	78.91	82.23	80.30	1.02
	SVR	10.43	11.76	11.13	0.36	86.73	89.78	88.14	0.85
VV+VH+NDPI+API	LR	13.37	14.68	14.24	0.27	78.14	81.49	79.14	1.01
	SVR	10.40	11.70	11.08	0.35	86.88	89.96	88.26	0.83
VV+RPI+NDPI+API	LR	13.20	14.13	13.74	0.28	79.60	82.85	80.88	1.00
	SVR	10.40	11.72	11.10	0.36	86.67	89.88	88.10	0.87
VH+RPI+NDPI+API	LR	13.13	14.14	13.76	0.30	79.65	82.96	80.79	1.02
	SVR	10.34	11.62	11.02	0.34	86.98	89.97	88.31	0.80
VV+VH+RPI+NDPI +API	LR	13.19	14.14	13.74	0.29	79.65	82.87	80.88	1.00
	SVR	10.35	11.66	11.05	0.36	86.90	90.03	88.28	0.85

Scenarios with 4 predictors and 5 predictors were unable to produce models with better accuracy than models with VH, NDPI, and API predictors. Therefore we found that the SVR model with 3 predictors was the best (Table 3).

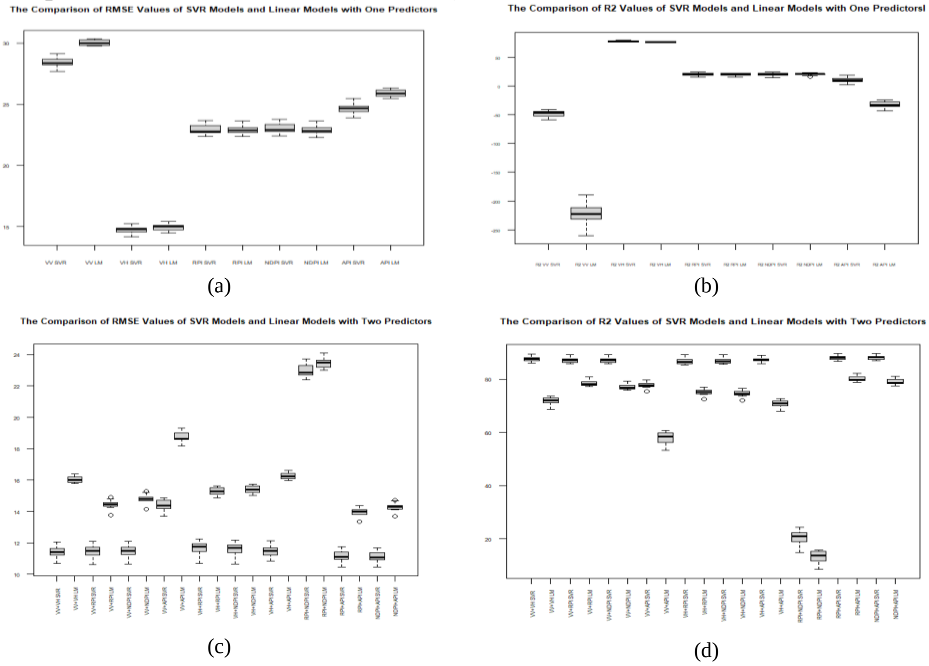

Figure 2. Boxplot of Ten Times Analysis Results

The results of 10 repetitions of training and testing data show that almost all of them show that the SVR method is better than the LR method. The SVR model provides more accurate and stable results than the LR model (Figure 3). The use of the RBF Kernel in the SVR method can accommodate complex nonlinear relationship problems (Moqaddasi Amiri et al., 2019) by submitting the problem to a higher spatial dimension so that the non-linear relationship becomes quite linear (Gaurav & Patel, 2020)

The selection of the model in this study can provide quite complete information in this study. It's just that when the number of predictors is very large, the scenarios carried out in this study become more difficult. Therefore the model selection strategy is like the stepwise parameter selection method, namely StepSVM (Guo & Chou, 2020). This method is claimed to be able to produce an accurate and consistent model. Another variable selection method that can be applied is the adaptive Fusion method for mixed kernel functions. This method is claimed to be able to produce models with good accuracy and easy to generalize (Wang & Xu, 2017).

The SVR method is capable of producing better model accuracy and stability than the LR method. This is certainly very necessary to produce information on the age of paddy in the field. However, implementing the SVR model is not as easy as implementing the LR model. This is because the SVR model has more parameters compared to the LR method. LR model parameters are easier to identify and apply as in research (Dirgahayu & Made Parsa, 2019) which uses sentinel-1 data to model the paddy phase. Therefore, applying the SVR method to field data to produce information is a challenge for researchers.

4. CONCLUSION

The SVR method provides better accuracy of paddy age modeling results compared to the LR method. To achieve good SVR model accuracy, at least two predictors are needed, such as VV and VH. The SVR model has better stability than the LR. Therefore, based on the accuracy and stability tests on the paddy age model using sentinel image data, it can be concluded that the SVR method is superior to the LR method.

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