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Mapping spatial drivers of rice productivity: A case study of Inpari 36 and 37 in West Java with BYM2-INLA

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Abstract

West Java is one of Indonesia's largest rice-producing provinces. However, rice production has declined by 23.07% since 2018 due to land conversion. Therefore, this study investigates the factors influencing rice productivity by modeling and mapping the productivity of Inpari 36 and Inpari 37 rice varieties using the Besag York Mollié 2 (BYM2) spatial model with Integrated Nested Laplace Approximation (INLA) inference. The response variable was rice productivity in 27 districts/cities in West Java, with explanatory variables including plant-disrupting organisms, pest-resistant organisms, altitude, average temperature, number of village unit cooperatives, number of tillers, and plant height. The results indicated significant spatial patterns, with the number of tillers and plant height positively affecting both varieties. Additionally, the number of village unit cooperatives had a significant effect on Inpari 36. These findings provide spatial-based recommendations for improving rice productivity and food security policies in West Java.

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INTRODUCTION

Food security is one of the important issues in a country's development process (Simatupang, 2007). The agricultural sector is important in realizing food security because of its role as the main food provider (Sumastuti, 2010). Food crop commodities, especially rice, are very important and strategic commodities because they are basic human needs that must be met (Farid et al., 2018). One of the provinces that contributes the largest rice production in Indonesia is West Java (BPS, 2022). Rice production in West Java on 2022 was recorded at 9,433,723 million tons, or 17,28% of the total rice production in Indonesia (BPS, 2022). However, rice production in West Java since 2018 has decreased by 23,07%, from 12.540.550 million tons to 9.647.359 million tons (BPS, 2018). One of the efforts made to increase rice productivity in West Java is by applying new

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superior varieties of rice, one of which is Inpari 36 and Inpari 37 Tungro-resistant (BSIP Jawa Barat, 2023).

Research that models rice productivity using spatial data is still relatively minimal (Gracia et al., 2024). Spatial analysis is the modeling of spatial interactions in a region based on weight values and additional effects (Bivand et al., 2014). Spatial analysis using bayes inference can model more complex phenomena using a hierarchical structure so that the resulting model allows for sharing characteristics based on adjacent areas for area data or based on distance for point data (Rachmawati & Pusponegoro, 2021). A frequently used spatial model is the Besag York Molliè (BYM) model (Besag et al., 1991). The model takes into account that data are spatially correlated and observations in adjacent areas are more similar than observations in more distant areas (Asmarian et al., 2019). This study uses the Besag York Mollie 2 spatial model which is a new parameterization of the BYM2 model (Simpson et al., 2017) and the inference used is Integrated Nested Laplace Approximation (INLA), which is an alternative method that can overcome convergence problems in Markov Chain Monte Carlo (Rue et al., 2009). INLA is designed with a latent gaussian model that provides more accurate results in a shorter time (Rachmawati & Pusponegoro, 2021). INLA has been widely used to analyze spatial or temporal data using the Bayes approach such as modeling the number of suicides in London into a spatial model assuming a Poisson distribution (Blangiardo et al., 2013), analyzing the spatio-temporal incidence of stomach cancer in southern Portugal (Papoila et al., 2014) and in Indonesia including modeling poverty in Java using Bayesian Spatial Probit (Maulina et al., 2019).

Based on a literature review, there has been no prior research applying the Besag York Mollié 2 (BYM2) model with the Integrated Nested Laplace Approximation (INLA) approach to map rice productivity in West Java (Dejene & Terdik, 2024). Moreover, spatial mapping specifically focused on newly introduced rice varieties, such as Inpari 36 and Inpari 37, remain largely unexplored. Therefore, this study seeks to fill this research gap by modeling and mapping the productivity of Inpari 36 and Inpari 37 rice varieties using the BYM2 spatial model, whose inference is based on INLA (Kadupitiya et al., 2022). The analysis considers regional aspects using Bayesian spatial modeling (Suphannachart, 2018). Section 2 of this paper explains the BYM2 components that assume spatial dependence. Section 3 discusses the spatial modeling results for Inpari 36 and Inpari 37 rice productivity at the city/district level and highlights the significant explanatory variables. The final section presents the spatial regression model along with policy recommendations.

METHOD

This research uses quantitative research methods. The research design conducted in this study has a statistical analysis design because the secondary data obtained will be processed and modeled with statistics using the Besag York Mollié 2 (BYM2) spatial model. In this study, the data used is cross-section data shown from Inpari 36 and Inpari 37 rice productivity data obtained in 2023. The data was obtained from the website and publications of the Central Statistics Agency (BPS), the West Java Agricultural Instrument Standardization Agency (BSIP), and the Agricultural Statistics Database (BDSP) in 2023. The response variable y was the productivity of Inpari 36 and Inpari 37 rice in West Java. The explanatory variables used were plant disrupting organisms (Sudewi et al., 2020), pest resistant organisms (Temaja et al., 2015), altitude of the region (Nuryanto et al., 2014), average temperature (Jaisyurahman et al., 2020), number of village unit cooperatives (Kadek et al., 2023), number of tillers (Yulina et al., 2021), and average plant height (Yulina et al., 2021).

The spatial Bayes regression model consists of fixed effects in the form of explanatory variables, then consists of random effects, namely spatially structured random effects and spatially unstructured random effects (Blangiardo et al., 2013). The equation model can be written as follows:

$$\eta_i = \log(\rho_i) = \alpha + \sum_{m=1}^{M} \beta_m x_{mi} + u_i + v_i \tag{1}$$

y_i is the productivity of rice in the region i, α represents intercept, coefficient $\beta = \{\beta_1, \dots, \beta_M\}$ measures the effect of multiple covariates, $x = x_1, \dots, x_M$. In spatial modeling that has been produced there are spatial structured residuals and unstructured spatial residuals. Both residuals were obtained from the conditional autoregressive model with Besag-York-Mollie (BYM) specifications. The conditional autoregressive model is included in the area approach to accommodate spatial dependence in error (Larasati & Hajarisman, 2020). The BYM specification will be entered through the conditional autoregressive model. The BYM model is widely used in modeling and Bayesian case mapping. Conditional autoregressive models defined as prior modeled as follows:

$$u_i | u_{j \neq i} \sim Normal\left(\frac{\sum_{j \in N(i)} u_j}{\# N(i)}, \frac{\sigma^2}{\# N(i)}\right) \quad (2)$$

u_i is a spatial structured residuals where $\# N(i)$ is the number of regions that share boundary with the i-th region (the neighbor of the region). v_i is an unstructured residual spatial modeled by $v_i \sim Normal(0, \sigma^2)$. Simpson et al., (2017) proposed a new parametrization of the BYM model that makes the parameters interpretable by the Penalized Complexity (PC) prior to assignment. The BYM2 model utilizes a scaled spatially structured random component $\boldsymbol{u}_*$ and unstructured random components $\boldsymbol{v}_*$.

$$\boldsymbol{b} = \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}\boldsymbol{v}_* + \sqrt{\phi}\boldsymbol{u}_*\right). \quad (3)$$

Precision parameters $\tau_b > 0$ controls the contraction of the marginal variance of the weighted sum $\boldsymbol{u}_*$and $\boldsymbol{v}_*$. Mixing parameters $0 \leq \phi \leq 1$ measures the proportion of marginal variance explained by structured effects $\boldsymbol{u}_*$. Thus, the BYM2 model is the same as the single spatial model when $\phi = 1$, and unstructured spatial models when $\phi = 0$. To create a posterior mean map of the random effects $\boldsymbol{b}$ BYM2, this research used 27 first row in mean (Moraga, 2020).

RESULTS AND DISCUSSIONS

Inpari 36 and Inpari 37 are the latest rice VUBs resistant to tungro disease, released by the Agricultural Research and Development Agency (Balitbangtan) in collaboration with Lolittungro and Big Rice Center. Inpari 36 and 37 are presented in Figure 1. and Figure 2.

Figure 1. Inpari 36

Figure 2. Inpari 37

The advantages of Inpari 36 and Inpari 37 include excellent yields, more tillers and plant height, resistance to blast and tungro diseases, and fluffy rice texture. West Java rice productivity is expected to increase as a result of the advantages of VUB Inpari 36 and Inpari 37. The differences between Inpari 36 and Inpari 37 rice are presented in Table 1. Based on data from the Agricultural Research and Development Agency (2021), it shows that these two varieties have advantages with an average yield of 6.3-6.7 tons/ha GKG and a potential yield of 9.1-10.0 t/ha GKG. The cultivars' relatively young age of 114 days after seedling, upright flag leaves that deter birds, thin grain shape, fluffy rice texture, and resistance to blast and tungro (BSIP Jawa Barat, 2023).

Table 1. Differences between Inpari 36 and Inpari 37

Description	Inpari 36	Inpari 37
Plant age	±114 hss	±114 hss
Plant height	±113 cm	±111 cm
Number of grains per panicle	±111 items	±105 items
Average yield	±6,7 t/ha GKG	±6,3 t/ha GKG
Potential yield	10 tons/ha GKG	9,1 tons/ha GKG
Planting recommendations	Suitable for planting in irrigated rice field ecosystem up to altitude < 600 masl	Suitable for planting in lowland irrigated rice field ecosystems up to an altitude of < 600 masl

Mathematical modeling of Inpari 36 rice productivity that specifically showed the details of the estimated value using the BYM2 model was presented in Table 1. Table 1 showed that the number of plants disrupting organisms (x_1), number of pest-resistant organisms (x_2), as well as the altitude of the region (x_3) had negatively affects the productivity of Inpari 36 rice, which was mean that the variable could reduce the productivity of Inpari 36 rice. Meanwhile, the average temperature (x_4), number of village unit cooperatives (x_5), number of tillers (x_6), and the average plant height (x_7) had a positive effect on the productivity of Inpari 36 rice, which was mean that the variable could increase the productivity of Inpari 36 rice.

Table 2. Coefficient of Fixed Effect Inpari 36

Variable	Mean	Credibility Interval
α	-1.479	(-3.373, 0.417)
x_1	-0.004	(-0.014, 0.006)
x_2	-0.032	(-0.080, 0.016)
x_3	-0.014	(-0.356, 0.319)
x_4	0.014	(-0.024, 0.053)
x_5	0.009	(0.002, 0.016)
x_6	2.030	(1.067, 3.007)
x_7	2.185	(0.977, 3.384)

The spatial modeling results in Table 2 above can be expressed in the regression equation, namely:

$$\eta_i = \log(\rho_i) = -1.479 - 0.004\, x_1 - 0.032\; - 0.014\, x_3 + 0.014\, x_4 + 0.009\, x_5 + 2.030\, x_6 + 2.185\, x_7 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}\boldsymbol{v}_* + \sqrt{\phi}\,\boldsymbol{u}_*\right) \quad (4)$$

Equation (4) uses a Bayes spatial regression model with a log link function, so it must be returned to its original value. The number of plants disrupting organisms (OPT) has a mean value of -0.004 can be interpreted that the addition of 0.01 units or 100 number of OPT, it can reduce the productivity of Inpari 36 rice by 0.996 = exp(-0.004) tons/ha. Meanwhile, the pest−resistant organism variable has a mean value of -0.032 can be interpreted that the addition of 0.01 units or 100 numbers of pest-resistant organisms can reduce the productivity of Inpari 36 rice by 0.9685 tons/ha. Regional elevation has a mean value of -0.014 which can be interpreted that the addition of 0.001 units or 1000 masl can reduce the productivity of Inpari 36 rice by 0.9861 tons/ha. Meanwhile, the average temperature has a mean value of which means that each addition will increase the productivity of Inpari 36 rice by 1.014 tons / ha. The number of village unit cooperatives (KUD) has a mean value of 0.009 which means that the addition of 1 unit of cooperatives can increase the productivity of Inpari 36 rice by 1.009 tons/ha. The number of tillers has a mean value of 2.030 can be interpreted that the addition of 0.01 units or 100 tillers can increase the productivity of Inpari 36 rice by 7.614 tons/ha. Meanwhile, the average plant height has a mean value of 2.185 which means that the addition of 1 m or 100 cm in the average plant height can increase the productivity of Inpari 36 rice by 8.891 tons/ha. Based on the credibility interval, it can be seen that the variable was the number of village unit cooperatives (x_5), number of tillers (x_6), and the average plant height (x_7) had significant effect on Inpari 36 rice productivity.

Mathematical modeling of Inpari 37 rice productivity was presented in Table 2. Table 2 showed that the variable that had a negative sign was the number of plant-disrupting organisms (x_1), number of pest-resistant organisms (x_2), as well as the altitude of the region (x_3). This means that this variable could reduce Inpari 37 rice productivity. Meanwhile, the variable that had a positive sign was the average temperature (x_4), the number of village unit cooperatives (x_5), number of tillers (x_6), and the average plant height (x_7). This means that these variables could increase the productivity of Inpari 37 rice. From the credibility interval, it can be seen that only the number of tillers (x_6), and the average plant height (x_7) had a significant effect on the productivity of Inpari 37 rice.

Table 3. Coefficient of Fixed Effect Inpari 37

Variable	Mean	Credibility Interval
α	-1.007	(-3.270, 1.263)
x_1	-0.006	(-0.019, 0.007)
x_2	-0.010	(-0.069, 0.049)
x_3	-0.017	(-0.442, 0.400)
x_4	0.005	(-0.046, 0.055)
x_5	0.001	(-0.009, 0.011)
x_6	1.339	(0.011, 2.664)
x_7	2.398	(0.414, 4.386)

The spatial modeling results in Table 3 can be expressed in the regression equation as follows.

$$\eta_i = \log(\rho_i) = -1.007 - 0.006\,x_1 - 0.010\,x_2 - 0.017x_3 + 0.005\,x_4 + 0.001\,x_5 + 1.339\,x_6 + 2.398\,x_7 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}\boldsymbol{v}_* + \sqrt{\phi}\,\boldsymbol{u}_*\right) \quad (5)$$

Equation (5) was obtained from the model used in this research, namely spatial Bayes regression, which used the log link function, so the model obtained from Table 2 must be returned to its original value. The number of plant pest organisms (OPT) had a mean value of −0.006, which means that the addition of 0.01 units or 100 numbers of pests could reduce Inpari 37 rice productivity by 0.994 tons/ha. Meanwhile, pest-resistant organisms had a mean value of −0.010 means that the addition of 0.01 units or 100 OTH amounts could reduce Inpari 37 rice productivity 0.99 tons/ha. The height of the area had a mean value of −0.017, which could be interpreted as an addition 0.001 units or 1000 meters above sea level could reduce Inpari 37 rice productivity by 0.9831 tons/ha. Meanwhile, the average temperature has a mean value of 0.005, which means that every additional 1°C would increase Inpari 37 rice productivity by 1.005 tons/ha. The number of village unit cooperatives (KUD) had a value 0.001, which means that the addition of 1 KUD unit could increase Inpari 37 rice productivity by 1,001 tons/ha. The number of tillers had a mean value of 1.339, which means that an addition of 0.01 units or 100 number of tillers could increase Inpari 37 rice productivity by 3,815 tons/ha. Meanwhile, the average plant height had a mean value of 2.398, which means that the addition of 1 m or 100 cm to the average plant height could increase Inpari 37 rice productivity by 11 tons/ha.

The spatial pattern used the BYM2 model, which was a new parametrization of the BYM model, which used periodic spatially structured random components $\boldsymbol{u}_*$ and an unstructured random component $\boldsymbol{v}_*$ (Moraga, 2020). The random effect value b from BYM2 can be seen in Table 3. If, the value of $\mathbf{b} < 0$ means productivity in specific region less than the average and the value of $\mathbf{b} > 0$ means productivity in specific region more than the average.

Table 4. Random effect value **b** of BYM2

ID	Regency	Random Effect Value b	
		Inpari 36	Inpari 37
1	Bandung	0.025	0.038
2	Bandung Barat	0.07	0.003
3	Bekasi	-0.1386	-0.266
4	Bogor	-0.051	0.016
5	Ciamis	-0.015	-0.011
6	Cianjur	0.051	0.056
7	Cirebon	-0.007	0.022
8	Garut	0.008	0.023
9	Indramayu	0.157	0.264
10	Karawang	-0.017	0.157
11	Bandung City	0.03	0.025
12	Banjar City	-0.091	0.046
13	Bekasi City	-0.182	-0.094
14	Bogor City	0.09	0.004
15	Cimahi City	0.017	0.066
16	Cirebon City	-0.139	-0.081
17	Depok City	-0.076	0.022
18	Sukabumi City	0.104	0.049
19	Tasikmalaya City	-1.33	-0.194
20	Kuningan	0.007	-0.023
21	Majalengka	0.083	0.075
22	Pangandaran	0.027	-0.076
23	Purwakarta	0.148	0.112
24	Subang	0.036	-0.206
25	Sukabumi	0.078	0.036
26	Sumedang	0.019	0.012
27	Tasikmalaya	-0.102	-0.079

Table 4 showed that 16 areas produced value $\mathbf{b} > 0$ for Inpari rice productivity 36. Meanwhile, 18 areas produced $\mathbf{b} > 0$ for Inpari rice productivity 37. This can be seen more clearly in the thematic map presented in Figure 3 and Figure 4.

Figure 3. interpreted the posterior mean map of Inpari 36 from the BYM2 model, which showed that there was a pattern on the map shown in green-colored areas that were close to each other. In Figure 3, the adjacent areas that produce patterns were Sukabumi City, Sukabumi, Cianjur, West Bandung, Cimahi City, Bandung City, Bandung, Garut, Purwakarta, Subang, Sumedang, Majalengka, Indramayu, and Kuningan. This showed the formation of clustering patterns in certain districts/cities in West Java. Figure 4 showed the posterior mean map of Inpari 37 from the BYM2 model by producing a pattern on the map shown in green areas. Regions that produce patterns in Figure 4 were Bogor City, Bogor, Sukabumi City, Sukabumi, Cianjur, West Bandung, Cimahi City, Bandung City, Bandung, Garut, Sumedang, Majalengka, Cirebon, Indramayu, and Karawang. The figure showed clustered patterns, indicating that neighboring locations might have similar values or productivity.

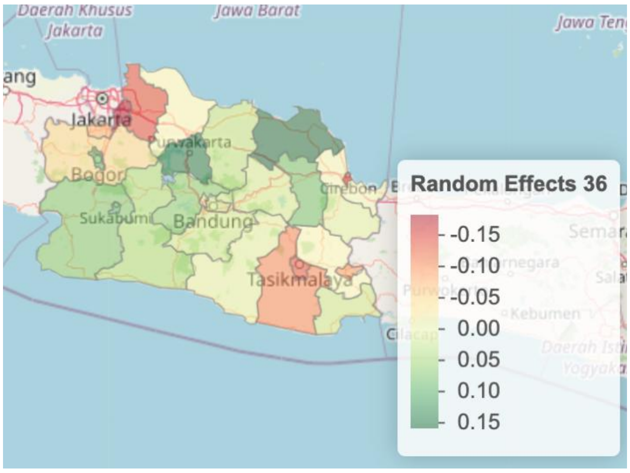

Figure 3. Posterior Mean Inpari 36

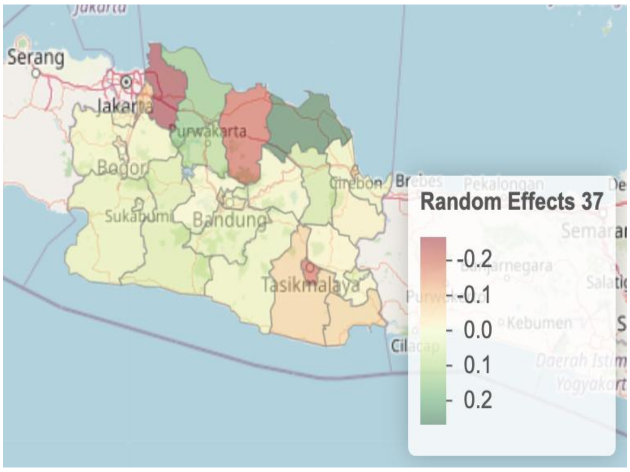

Figure 4. Posterior Mean Inpari 37

In order to improve food security in Indonesia, especially in West Java, this study also provides recommendations for government policies that can increase rice yields evenly in 27 districts and cities in West Java based on spatial mapping resulted in this reserach.

Table 5. Policy Recommendation

Policy Objective	Recommendation
Increase rice productivity	1) Using new superior varieties Inpari 36 and Inpari 37 that have been disseminated by BSIP West Java. 2) Implementing agricultural technologies such as efficient irrigation i.e. technical irrigation, use of fertilizers and pesticides, and use of tools and machinery.
Coping with plant-disrupting organisms and pest-resistant organisms	Plant-disrupting organisms and pest-resistant organisms hac a negative effect on rice productivity, which means that they could reduce rice productivity figures. The addition of 100 numbers of plant disrupting organisms would reduce the productivity of Inpari 36 rice by 0.996 tons/ha and by 0.994 tons/ha for Inpari 37. Meanwhile, the addition of 100 numbers of pest resistant organisms would reduce the productivity of Inpari 36 rice by 0.9685 tons/ha and by 0.99 tons/ha for Inpari 37. Although these variables did not significantly affect rice productivity, farmers must prepare ways to overcome plant-disrupting organisms and pest-resistant organisms. The efforts that can be made are as follows.

Policy Objective	Recommendation
	1) Performing control principles with crop cultivation, namely: a. Plant spacing; b. Tillage; c. Sanitization; d. Correct and regular fertilization; e. Appropriate use of insecticides. 2) Planting rice varieties takes into account the location and growing season specifications for each variety.
Anticipating climate change	Altitude had a negative effect on rice productivity, which means it could reduce rice productivity. The addition of 1000 masl could reduce the productivity of Inpari 36 rice by 0.9861 tons/ha and by 0.9831 tons/ha for Inpari 37. Meanwhile, the average temperature had a positive effect on rice productivity. The addition of 1°C could increase the productivity of Inpari 36 rice by 1.014 tons/ha and by 1.015 tons/ha for Inpari 37. This was in accordance with research conducted (Lestari et al., 2015) that as altitude increases, air pressure decreases. Although this variable did not have a significant effect on rice productivity, farmers must prepare for an increase in air temperature and humidity that will result in climate change that has an impact on the growth and development of plant pest organisms that can harm crop yields. In addition, farmers must also be prepared in the event of an *El-Nino* drought that results in a lack of water supply, making them vulnerable to crop failure.
Establishing village unit cooperatives	The number of village unit cooperatives had a positive effect on rice productivity, which means that it could increase the rice productivity rate. The addition of 1 village unit cooperative could increase Inpari 36 rice productivity by 1.009 tons/ha and by 1.001 tons/ha for Inpari 37. This variable had a significant effect in the case of Inpari 36 rice productivity, so the government can consider building village unit cooperatives in areas where there are no KUDs to improve the welfare of farmers, which is one of the benchmarks in rice productivity figures. In addition, village unit cooperatives also play a role as a means of rice production or as a marketing place so that it can be distributed to farmer groups.
Increase the number of tillers and average plant height	The number of tillers and average plant height had a positive effect on rice productivity, which means that they could increase the value of rice productivity. The addition of 100 tiller numbers could increase the productivity of Inpari 36 rice by 7.614 tons/ha and by 3.815 tons/ha for Inpari 37. Meanwhile, the addition of 100 cm of average plant height could increase the productivity of Inpari 36 rice by 8.891 and by 11 tons/ha for Inpari 37. This variable had a significant effect on rice productivity, so efforts were needed so that the number of tillers and average plant height increased. 1) The use of the right planting system, namely jajar legowo 2: 1 or 4: 1, has a significant effect because it affects the space for plant movement and competition in seizing nutrients and water in the soil and sunlight for photosynthesis. 2) The use of manure or NPK fertilizer can have an effect in increasing the number of tillers and average plant height.

Spatial modeling with BYM2 produces a spatial regression equation that identifies significant variables influencing the productivity of Inpari 36 and Inpari 37 rice (Kunimitsu et al., 2016). Spatial mapping shows clustered patterns across districts/cities in West Java, which can be used as a reference for policy formulation. Explanatory variables such as number of tillers, average plant height, and the number of village unit cooperatives significantly affect Inpari 36 productivity, while number of tillers and plant height affect Inpari 37. In order to improve food security in Indonesia, especially in West Java, this study also provides recommendations for government policies based on spatial mapping results in 27 districts and cities (Sucharidtham & Wannapan, 2021).

CONCLUSION

Spatial modeling with BYM2 produces a spatial regression equation. The case of Inpari 36 rice productivity is:

$$\eta_i = -1.479 - 0.004\, x_1 - 0.032\, x_2 - 0.014\, x_3 + 0.014\, x_4 + 0.009\, x_5 + 2.030\, x_6 + 2.185\, x_7 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}\boldsymbol{v}_* + \sqrt{\phi}\,\boldsymbol{u}_*\right) \tag{6}$$

The case of Inpari 37 rice productivity is:

$$\eta_i = -1.007 - 0.006\, x_1 - 0.010\, x_2 - 0.017 x_3 + 0.005\, x_4 + 0.001\, x_5 + 1.339\, x_6 + 2.398\, x_7 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}\boldsymbol{v}_* + \sqrt{\phi}\,\boldsymbol{u}_*\right) \tag{7}$$

Spatial mapping patterns obtained from random effect values are visualized on the average posterior map of Inpari 36 and Inpari 37 from the BYM2 model. Adjacent areas that produce spatial mapping patterns in Inpari 36 are Sukabumi City, Sukabumi, Cianjur, West Bandung, Cimahi City, Bandung City, Bandung, Garut, Purwakarta, Subang, Sumedang, Majalengka, Indramayu, and Kuningan. Meanwhile, the spatial mapping areas for Inpari 37 are Bogor City, Bogor, Sukabumi City, Sukabumi, Cianjur, West Bandung, Cimahi City, Bandung City, Bandung, Garut, Sumedang, Majalengka, Cirebon, Indramayu, and Karawang. The clustered pattern indicates that locations in close proximity may have similar values or productivity. These areas can be recommended to support food security in West Java. The explanatory variables that have a significant effect on the productivity of Inpari 36 rice are the number of tillers, average plant height, and the number of cooperatives. While the explanatory variables that significantly affect the productivity of Inpari 37 rice are the number of tillers and average plant height.

For future research, we suggest comparing the BYM2-INLA approach with other spatial modeling methods such as spatial Durbin or spatio-temporal models, especially when longitudinal rice productivity data becomes available (Sailaja et al., 2019). Additionally, integrating socio-economic variables or remote sensing indices may enhance prediction accuracy and policy relevance.

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