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Spatial pattern and determinants of village level poverty in Marinduque Island, Philippines

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Abstract This study explored the spatial pattern and potential determinants of village level poverty in the province of Marinduque, Philippines. Using published topographic, climatic, and socio-economic variables it applied spatial analysis, ordinary least squared regression, and geographically weight regression (GWR) to determine patterns and factors affecting poverty in the province. Based on the results, clusters of high-high and low-high poverty incidences were present in the province. Also, out of the 18 variables tested, only 5 variables showed significant effect on poverty incidence. These variables are slope, annual rainfall, population growth rate, distance to town centers, and distance to ports. However, GWR result showed that the impact of these variables to poverty in the province varies by villages. Slope and annual rainfall were the two variables that showed greater effect to village level poverty incidence suggesting that poverty in the province is highly influenced by its current agricultural productivity.

Keywords Poverty · Spatial analysis · GWR · Agricultural productivity · Marinduque · Philippines

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Introduction

Poverty is one of the biggest problems a developing country (Churchill and Smyth 2017). In the case of the Philippines, poverty has been a perennial problem (ADB 2009). According to the report of the Asian Development Bank (ADB 2009), although there have been a decrease in poverty incidence in the country, such reduction is slower than its neighboring countries. Among the Southeast Asian countries, poverty incidence in the Philippines (21.6%) ranks high along with Myanmar (25.6%) and Lao PDR (23.2%) compared to countries such as Cambodia (14%), Indonesia (10.6%), Thailand (10.5%), and Vietnam (7.0%) (ADB 2017).

According to Albert and Collado (2004), poverty in the Philippines is measured based on income data from the family income and expenditure survey (FIES). The FIES is a household survey conducted every 3 years by the Philippine national statistics office (PNSO).[1] Poverty lines or thresholds are generated based on per capita minimum food and non-food requirements. Separate poverty threshold were computed for urban and rural areas of each province in the country. Based on the computed poverty threshold, a household is

[1] In 2013 the Philippine National Statistics Office was merge with other government agencies such National Statistical Coordination Board, the Bureau of Agricultural Statistics, and the Bureau of Labor and Employment Statistics to create the Philippine Statistics Authority.

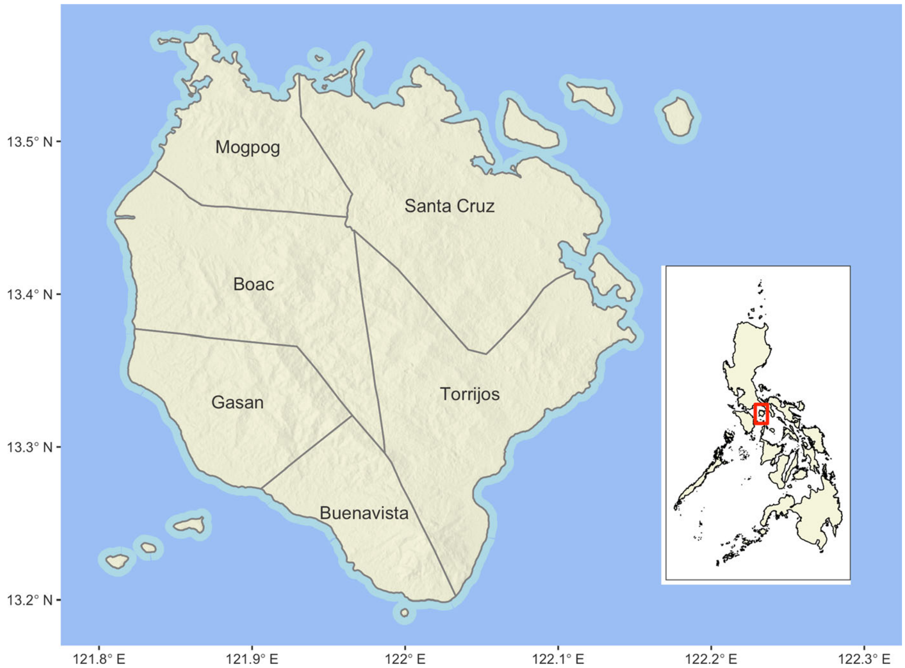


Fig. 1 Location map of Marinduque, Philippines

classified as poor if its per capita income is less than the poverty threshold calculated for the specific area where the household is located. According to the Philippine Statistics Authority, in 2015, the annual per capita poverty threshold in the Philippines is Php 21,753 (USD 410)[2] or approximately USD 1.1 per day (PSA 2016).

Several studies been conducted to study poverty in the Philippines. Albert (2007) reported that human capital, household size, education, and occupation are important determinants of poverty in the country. Almaden (2015) observed lower poverty intensity in households with higher financial, human, and social capital. Vista and Murayama (2011) reported that elevation, slope, rainfall, proximity to major markets, land distribution, fiscal population, and population growth are significant determinants of poverty in two provinces in the Philippines (Camarines Sur, and Albay). According to ADB (2005, 2009) the main cause of poverty in the Philippines can be generalized into macroeconomic problems, employment issues, agricultural productivity, rapid population, growth, physical disability, and government concerns (i.e. corruption, and armed conflict). Similar observations were reported by Dowling and Chin-Fang (2009) adding human capital and natural shocks, investment climate and gradual loss of international competitiveness, and frequent changes in government policies as determinants of poverty in the country. However, one of the key findings of ADB (2009) is that poverty levels in the country vary greatly by regions. Therefore poverty-targeting program should be reliable, accurate, and timely at the local level (ADB 2009).

Spatial mapping of poverty allows the integration of socio-economic indicator and biophysical information which provides a more analytical and systematic

Table 1 Area, area coverage, and income class, of six municipalities of Mariduque (Data Source: Salvacion and Macandog 2015)

Municipality	Area (ha)	Percentage of area	Income class
Boac	21,265	22.17	1st
Buenavista	7860	8.19	4th
Gasan	11,930	12.44	3rd
Mogpog	8780	9.15	3rd
Sta. Cruz	24,660	25.71	1st
Torrijos	21,430	22.34	3rd

[2] Conversion of peso to dollar was based on Php 53.04 peso to dollar exchange rate.

image of equity and human wellbeing (Henninger and Shel 2002; Vista and Murayama 2011). In addition, geographic targeting of small administrative areas showed more efficiency in reaching the poor and cost effectiveness in terms of development spending (Baker and Grosh 1994; Bigman et al. 2000; Elbers et al. 2003; Hyman et al. 2005; Wang and Zhang 2017). However, the role of spatial patterns and processes in poverty assessment has received little attention (Hyman et al. 2005). In the Philippines, poverty studies are concentrated within the realm of economics and public policy (Vista and Murayama 2011).

Table 2 List of independent variables used potential determinants of poverty incidence in the province of Marinduque

Variable	Type	Source
Unemployment Rate (Year 2005)	Socioeconomic	CBMS
Unemployment Rate (Year 2008)	Socioeconomic	CBMS
Unemployment Rate (Year 2015)	Socioeconomic	CBMS
Population Growth Rate (1990–2015)	Socioeconomic	Calculated from CENSUS data
Population Growth Rate (1995–2015)	Socioeconomic	Calculated from CENSUS data
Population Growth Rate (2000–2015)	Socioeconomic	Calculated from CENSUS data
Population Growth Rate (2007–2015)	Socioeconomic	Calculated from CENSUS data
Population Growth Rate (2010–2015)	Socioeconomic	Calculated from CENSUS data
Elevation	Topographic	ASTER-GDEM
Slope	Topographic	Derived from ASTER-GDEM
Distance from provincial coastline	Geographic	Calculated from boundary map
Distance from provincial highway	Geographic	Calculated based OSM road network data
Distance from health facilities	Geographic	Calculated from georeferenced maps
Distance from the ports	Geographic	Calculated from georeferenced maps
Distance from town centers	Geographic	Calculated from georeferenced maps
Percentage of agricultural land	Land cover	Calculated from NAMRIA land cover data
Annual Rainfall	Climatic	WorldClim Database

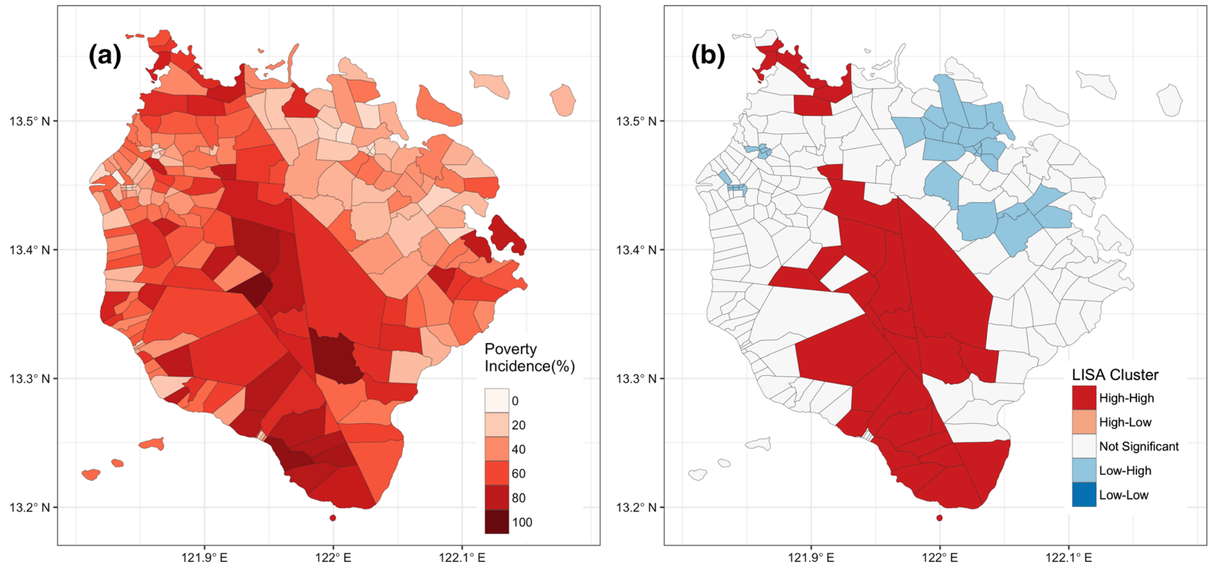


Fig. 2 Spatial distribution (**a**) and local spatial clusters (**b**) of poverty incidence in Marinduque

Marinduque (Fig. 1) is an island province located 200 km south of the Manila, which is the capital of the Philippines. The province is consists of 6 municipalities covering 96 thousand hectares of land (Table 1). On the average, the province is around 204 masl with mountainous regions occupying its inner portion and low-lying areas on the outer part (Salvacion 2016). The terrain of the province is dominated by rolling to moderately steep (approximately 66%) slopes (Salvacion 2016). Farming and fishing are the major sources of livelihood in the province (Salvacion and Magcale-Macandog 2015). Based on the report of Reyes et al. (2017), the average poverty incidence per village in Marinduque is around 46.11%. This figure is very far from the "No Poverty" target of the sustainable development goals (SDG) adopted by the United Nations (https://sustainabledevelopment.un.org/). This study assessed the spatial pattern and potential determinants of poverty in the province of Marinduque.

Methodology

Data

Village level poverty incidence data and other socio-economic data were derived from community based monitoring system (Reyes and Due 2009) report for the province of Marinduque for the year 2015 (Reyes et al. 2017). Data on elevation was extracted from advanced space-borne thermal emission and reflection radiometer (ASTER) global digital elevation model (GDEM) (Abrams 2000; Abrams et al. 2015) website (http://gdem.ersdac.jspacesystems.or.jp/). Data on slope was derived from this elevation data. Land use/cover data were obtained from the national mapping and resource information agency (NAMRIA, http://www.namria.gov.ph). Road network map was downloaded from OpenStreetMap (www.openstreetmap.org). Location of health facilities, ports, and town centers were georeferenced using google maps (https://maps.google.com/). Distances from these facilities and to road networks were calculated using *distance* function of R *raster* package. Table 2 shows the list of variables used in this study.

Data analysis

Village level poverty incidence data were analyzed for spatial autocorrelation using both global (Jackson et al. 2010; Young and Jensen 2012) and local (Anselin 1995) test for spatial association to identify potential spatial clusters of poverty in the province. Then, multiple linear regression was used to determine which among the independent variables significantly affects poverty incidence in Marinduque. A full model

Table 3 Local clusters of high-high poverty incidence in Marinduque, Philippines

Municipality	Village	Poverty incidence (%)
Boac	Bayuti	75.5
Boac	Binunga	79.7
Boac	Boi	96.2
Boac	Duyay	65.6
Boac	Hinapulan	87.1
Boac	Mahinhin	74.0
Boac	Sabong	68.4
Boac	Tambunan	71.9
Boac	Tumagabok	81.3
Buenavista	Bagacay	83.1
Buenavista	Bagtingon	82.6
Buenavista	Bicas-Bicas	85.7
Buenavista	Caigangan	82.2
Buenavista	Libas	91.9
Buenavista	Malbog	69.2
Buenavista	Sihi	62.3
Buenavista	Timbo	82.1
Buenavista	Tungib-Lipata	76.3
Buenavista	Yook	81.6
Gasan	Tabionan	68.4
Mogpog	Argao	73.0
Mogpog	Guisian	64.4
Mogpog	Hinanggayon	64.8
Mogpog	Malayak	78.8
Mogpog	Mendez	72.3
Mogpog	Paye	69.2
Mogpog	Sayao	76.9
Torrijos	Dampulan	56.2
Torrijos	Payanas	67.2
Torrijos	Sibuyao	68.1
Torrijos	Talawan	93.8

Table 4 Local clusters of low-high poverty incidence in Marinduque, Philippines

Municipality	Village	Poverty incidence (%)
Boac	Malusak	19.4
Boac	Mataas Na Bayan	18.3
Boac	Mercado	29.2
Boac	Murallon	25.5
Boac	Poras	4.3
Boac	San Miguel	3.3
Boac	Tampus	25.1
Mogpog	Dulong Bayan	27.7
Mogpog	Gitnang Bayan	14.4
Mogpog	Market Site	12.7
Mogpog	Nangka I	28.2
Mogpog	Villa Mendez	15
Santa Cruz	Aturan	16.4
Santa Cruz	Bagong Silang Poblacion	12.9
Santa Cruz	Baliis	36.2
Santa Cruz	Balogo	28.4
Santa Cruz	Banahaw Poblacion	17.2
Santa Cruz	Bangcuangan	21.1
Santa Cruz	Devilla	25.4
Santa Cruz	Dolores	21.9
Santa Cruz	Hupi	14.8
Santa Cruz	Jolo	25.3
Santa Cruz	Kilo-Kilo	47.3
Santa Cruz	Landy	12.5
Santa Cruz	Lapu-lapu Poblacion	22.3
Santa Cruz	Lipa	32
Santa Cruz	Lusok	20.5
Santa Cruz	Maharlika Poblacion	8.5
Santa Cruz	Manlibunan	28.2
Santa Cruz	Napo	16.8
Santa Cruz	Pag-Asa Poblacion	17.7
Santa Cruz	Pulong-Parang	22.5
Santa Cruz	Taytay	31.2

was constructed with poverty incidence as the dependent variable and all others as independent variables (Table 2). Then, a step-wise model selection was done based on Akaike Information Criterion (Akaike 1974) to reduce the number of independent variables and remove potential collinear relationship (Lachniet and Patterson 2006). Lastly, a geographically weight regression (GWR) model was fitted using the reduced number of independent variables. GWR is a statistical modeling technique that permits varying relationship between independents (predictors) and dependent (outcome) variables over space (Fotheringham et al. 2002; Matthews and Yang 2012). GWR has been widely used in spatial analysis in different fields (Matthews and Yang 2012; Ogneva-Himmelberger et al. 2009). In case of poverty mapping, Benson et al. (2005) used GWR to investigate potential spatial determinant of poverty incidence in Malawi. Using the same method, Apparicio et al. (2007) analyzed spatial pattern of poverty in Montreal. Ogneva-Himmelberger et al. (2009) used GWR to assess the relationship between poverty, percent of minority population

Table 5 Full model coefficients of different explanatory variables of poverty incidence in Marinduque

Variable	Coefficient	Standard error	*p value*
Unemployment rate (Year 2005)	0.0310	0.1118	0.7822
Unemployment rate (Year 2008)	0.0503	0.6851	0.9415
Unemployment rate (Year 2015)	0.1064	0.1851	0.5660
Population growth rate (1990–2015)	− 0.0724	0.0812	0.3738
Population growth rate (1995-2015)	0.3055	0.1138	0.0079*
Population growth rate (2000–2015)	0.0667	0.1349	0.6213
Population growth rate (2007–2015)	0.0597	0.1301	0.6469
Population growth rate (2010–2015)	− 0.0698	0.1593	0.6618
Elevation	− 0.0037	0.0242	0.8791
Slope	1.2930	0.4428	0.0039*
Distance from provincial coastline	0.0003	0.0007	0.7155
Distance from provincial highway	0.0000	0.0008	0.9602
Distance from health facilities	0.0007	0.0010	0.4743
Distance from the ports	0.0006	0.0003	0.0530*
Distance from town centers	0.0009	0.0009	0.3242
Percentage of agricultural land	− 1.0285	4.1862	0.8062
Annual rainfall	0.0369	0.0245	0.1342

p value followed by asterisk (*) is significant at $\alpha = 0.1$

Table 6 Reduced model coefficients of different explanatory variables of poverty incidence in Marinduque

Variable	Coefficient	Standard error	*p value*
Population growth rate (1995–2015)	0.2764	0.0474	0.0000
Slope	1.2956	0.2969	0.0000
Distance from the ports	0.0007	0.0002	0.0010
Distance from town centers	0.0014	0.0004	0.0010
Annual rainfall	0.0448	0.0147	0.0026

p value followed by asterisk (*) is significant at $\alpha = 0.1$

and impervious surface in the state of Massachusetts, USA. Recently, Slamet et al. (2017) applied GWR to model poverty indicators in Central Java, Indonesia.

Results

Spatial pattern of poverty incidence

Figure 2 shows the spatial distribution and pattern of village-level poverty incidence in Marinduque province. Based on Global Moran's I (0.45), presence of significant (*p value* < 0.01) clusters of high and low poverty incidence were observed (Fig. 2b). Local indicators of spatial associations (LISA) test showed that there were 31 High-High (Table 3) and 33 Low-High clusters (Table 4). Most of the villages included in the high-high clusters of poverty incidence were found in the municipalities of Boac and Buenavista. In the case of Boac, the High-High cluster constitute around16% of its total number of villages (61) while in the case of Buenavista, High-High clusters account for 67% of its total number of villages (15). Meanwhile, majority of the Low-High clusters were found in the municipality of Sta. Cruz. These villages constitute around 38% of the total villages in the municipality.

Regression analysis

Of the 18 explanatory variables of poverty incidence tested, only 3 variables showed significance (Table 5). These variables were slope, population growth rate

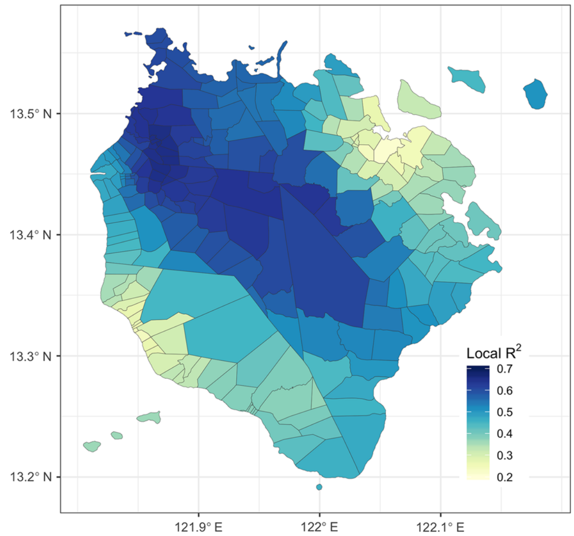


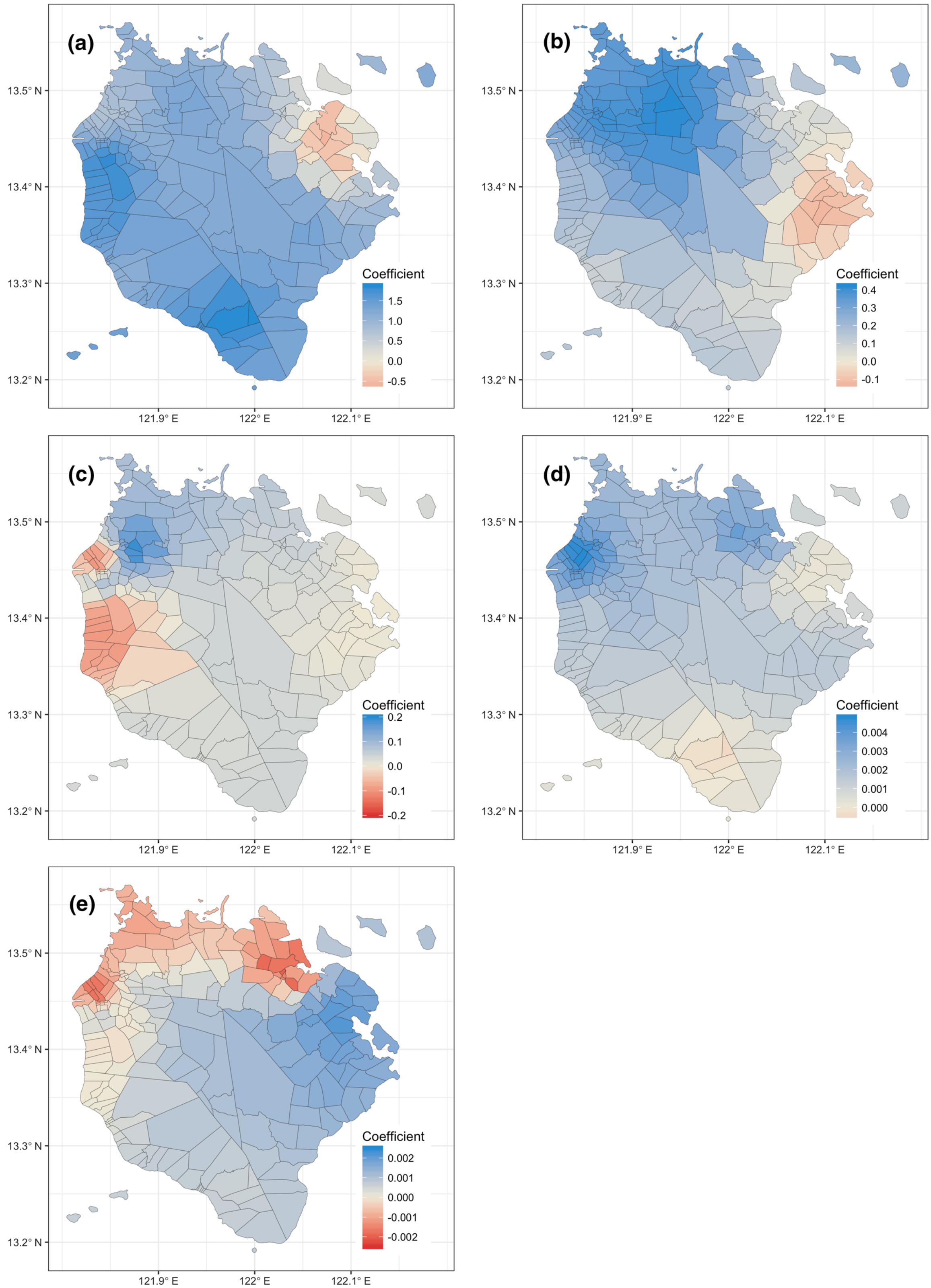
Fig. 3 Map of GWR Local R2

from 1995 to 2015, and distance to ports. Meanwhile, when the model was reduced using step-wise selection based on AIC criterion, the number of significant explanatory variables increased to 5 with the addition of distance from town centers, and annual rainfall (Table 6). There is also a slight increase in R^2 between the full model (0.38) and the reduced model (0.41). On the other hand, results from GWR showed varying R^2 (Fig. 3). The maximum computed R^2 was 0.66 while the lowest was 0.22. The coefficient for each explanatory variable also varies across the province (Fig. 4). Base on the GWR analysis, the slope has the largest computed regression coefficients followed by population growth rate from 1995 to 2015, annual rainfall, distance to town centers, and distance to ports. Positive contribution of slope to village level poverty incidence was high on the northwestern and southern portion of the province while the opposite was observed in northeastern portion (Fig. 4a). In the case of population growth rate from 1995 to 2015, contrasting effect were observed between the north and eastern portion of the province (Fig. 4b). Population growth rate from 1995 to 2015 positively contributes to the poverty incidence in the northern villages of the province but showing an opposite effect on the village in the eastern portion of Marinduque. The effect of annual rainfall is negative to poverty incidence of villages located in lowland areas in the municipalities of Boac, Mogpog, and Gasan (Fig. 4c). These are the areas where rice and corn were cultivated. Meanwhile, the opposite (positive) effect of rainfall on poverty incidence was observed in villages located on the mountainous portion of the municipality of Mogpog. The effect of distance to town centers was only evident in the villages of Boac, Mogpog, and Sta. Cruz (Fig. 4d). Lastly, the effect of distance to ports were only clear on the northern portion of the province where nearness to port negatively affect village level poverty incidence (Fig. 4e).

Discussion

Poverty is a negative social phenomenon that is inherently spatial in nature (Glasmeier 2002; Hyman et al. 2005; Michálek and Madajová 2018; Vista and Murayama 2011). Well-being of community and their neighboring areas are products of diffusion of innovations, social capital, trade, economies of scale, and other factors related to proximity and spatial interaction (Hyman et al. 2005). For example, according to Hyman et al. (2005) high living standards of a prosperous community usually have spill-over effect on its surrounding areas while high poverty areas are often surrounded by poor neighboring areas. Such is also true in the case of Marinduque showing contiguous cluster villages with high poverty incidence from the middle to southern portion as well as some small cluster of low poverty incidence on the northeastern and north western part of the province (Fig. 2b).

The effect of slope has been documented in other studies elsewhere. Okwi et al. (2007) reported that increasing slope contributes to increasing poverty rates in Kenya. Recently, Zhou and Xiong (2018) also reported that around 65% of poverty stricken counties in China are located in 9° to 18° of slope. A similar result was also reported by Vista and Murayama (2011)for the provinces of Camarines Sur and Albay, Philippines. According to Okwi et al. (2007) steep lands usually encounter problems with regards to cultivation, soil erosion, and irrigation. The same may be true in the case of Marinduque. Based on the 2016 national agricultural production data (PSA 2017) the average yield of coconut and banana (Saba variety) in the province are way below than the national average. The average yield of coconut, and banana in the province were around 2.05 tons/ha, and 1.44 tons/ha compared to the national average, 3.88 tons/ha


(a)
13.5° N
13.4° N
13.3° N
13.2° N
121.9° E
122° E
122.1° E
Coefficient
1.5
1.0
0.5
0.0
-0.5
(b)
Coefficient
0.4
0.3
0.2
0.1
0.0
-0.1
(c)
Coefficient
0.2
0.1
0.0
-0.1
-0.2
(d)
Coefficient
0.004
0.003
0.002
0.001
0.000
(e)
Coefficient
0.002
0.001
0.000
-0.001
-0.002

◀**Fig. 4** Local regression coefficients of **a** slope, **b** population growth rate, **c** annual rainfall, **d** distance to town centers, and **e** distance to ports

(coconut), and 13.56 tons/ha (banana), respectively. Such yield gaps can severely affect income and subsistence of farmers in the province (Tittonell and Giller 2013). Meanwhile, the effect of population growth on poverty has also been established elsewhere. Based on the Neo-Maltushian theory, the rapid increase in population can result to absolute poverty, and other negative societal impact (Ivanov 2017; Mellos 1988). Also, according to Sinding (2009) there is an increasing number of empirical studies providing evidence that countries with population policies and family planning programs in their economic development strategies have achieved high and sustained economic growth while reducing poverty. The effect of annual rainfall in the province of Marinduque can be explained in two ways. First, the negative effect of annual rainfall on the poverty incidence of villages in the lowland areas can be attributed to positive impact of rainfall on agricultural production in these areas. Second, the positive impact of annual rainfall on poverty incidence of villages on the mountainous region can be attributed to its topography, which as mentioned earlier is highly associated with problems in soil erosion, cultivation, and irrigation (Okwi et al. 2007; Vista and Murayama 2011). With regards to the impact of distance to town centers and poverty incidence, the result of this is similar to those of Ahlström et al. (2011), Vista and Murayama (2011), and Chen et al. (2015) where distance to town centers have positive impact to poverty incidence. According to Vista and Murayama (2011) presence of businesses, enterprises, offices, and higher educational institutions in city or town centers can affect the development of the nearby areas thus affecting its poverty incidence in those areas. However, Okwi et al. (2007) found the opposite with Wang et al. (2018) where distance to town centers has no impact on rural poverty in China. Lastly, with regards to the impact of distance to port in the poverty incidence this study has similar results with Yudhistira and Sofiyandi (2017). According to Yudhistira and Sofiyandi (2017) being closer to ports has positive impact on GDP per capita, labor productivity thus lowering poverty rate, and poverty gap.

Conclusion

This study assessed the spatial pattern and potential determinants of poverty incidence in the island province of Marinduque, Philippines. Result showed that village level poverty incidence tends to cluster in the province. Meanwhile, slope, annual rainfall, population growth rate, distance to town centers, and distance to ports were found to be significant predictors of poverty incidence in Marinduque. However, slope and annual rainfall were the two factors that showed greater influence to village poverty incidence in the province. This suggests that poverty in the province is highly influenced by agricultural productivity of the province. Such was supported by the apparent low yield level of some major crops in the province compared to the average national yield. Results from this study can be used as guide to design plans and programs to combat the problems of poverty in the province such as improvement of agricultural productivity, and voluntary family planning. In addition, such plans and programs can also be targeted to specific villages that showed higher coefficient with respect to each variable used in GWR modeling.

On the other hand, the result of this study is limited to the data sources (i.e. open-source or publicly available) and variables selected (Table 2) to explain poverty pattern in the province of Marinduque. Other factors such as politics (Andriesse 2017; de Dios 2007; Mendoza et al. 2012), land distribution or tenure (Vista et al. 2012), remittances (Quisumbing and McNiven 2010; Yang and Choi 2007), level of education (Almaden 2015), and other factors (Ofreneo 2015) that are not explored in this study is highly recommended.

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Compliance with ethical standards

Conflict of interest The author declare no conflict of interest.

Human and animals rights The research did not involve human participants or animals.

Informed consent The research did not involve the collection of any personally identifying data, nor anything that could be construed as identifying an individual, hence informed consent was not relevant.

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