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Measuring climate action readiness in maintaining ecological resilience using satellite imagery and field research in Garang Watershed, Central Java, Indonesia

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Abstract. *Sudarmanto B, Suranto S, Suntoro S, Sutrisno J. 2023. Measuring climate action readiness in maintaining ecological resilience using satellite imagery and field research in Garang Watershed, Central Java, Indonesia. Biodiversitas 24: 2958-2974.* The long-term viability of vegetation as a representation of land cover in a watershed is critical. However, more work is needed to develop vegetation management in the form of a climate action model that considers the existence of ecological and social values as a unified system, particularly in times of climate change. Moran's Index measurements and statistical correlation analysis were employed in this study to quantify geographical patterns. These measurements provide real-world judgment in developing aggressive climate response scenarios. Ecological values were derived from shifting vegetation trend indices due to mutual interaction between living beings that build a life cycle in harmony with the environment. Meanwhile, social values are determined by assessing individual internal factors such as attitudes, knowledge, and responses and external factors represented by local government institutions. The findings reveal that the distribution of residents and residential areas is dispersed. With a high confidence level, a linear index declines with R^2 = 0.5872 for inhabitants and R^2 = 0.9171 for residential areas. In the dry season, there is a significant relationship between the spatial pattern of vegetation indices and the inhabitant's index. The community's knowledge and attitudes considerably impact changes in vegetation indices, particularly during the rainy season, with R^2 = 0.207 for SAVI and 0.232 for NDVI. Community readiness values, which elaborate on knowledge, attitudes, responses, and the role of external institutions, show that community readiness in the upstream area of the watershed, specifically in the Kendal District, is in the best position, with a value of 6.627976. On the contrary, the Semarang District, the upstream area, has the lowest value of 4.257092.

Keywords: Climate action readiness, ecological values, social values, vegetation indices

INTRODUCTION

The role of vegetation in maintaining ecological resilience is crucial (Hugo Carrao et al. n.d.; Cecili et al. 2023; Alam et al. 2019). Although vegetation monitoring alone is insufficient to interpret land cover (LC) resilience comprehensively and still needs to be combined with other information, such as climate data, soil data, and land use data, to provide a more holistic understanding of the overall ecosystem condition. Therefore, vegetation monitoring can help identify changes in plant species composition and density, providing clues about the health and stability of land cover. Conversely, a decrease in vegetation density or changes in plant species composition can be indicators of disturbances in the ecosystem, such as erosion, soil degradation, or other environmental damage. Vegetation monitoring also helps monitor changes in the hydrological cycle. Vegetation is important in the water cycle and helps reduce floods and erosion risks. Therefore, vegetation density and diversity changes can provide clues about the land's ability to maintain stable land cover and reduce the risk of floods and erosion (Kidane et al. 2019; Tang et al. 2021; Kosmalla et al. 2022; Francke et al. 2022; Masroor et al. 2022).

The assessment of Land Use (LU), Land Cover (LC), and vegetation changes have become essential to various facets of the human and natural environment and the interaction between them (Kayiranga et al. 2016; Mohamed 2017; Aderele et al. 2020; Hegazy and Kaloop 2015; Alqurashi and Kumar 2013; El-Aziz 2013; Castro and Rocha 2015; Zubi 2022). The vegetation existence as a measure of ecological resilience is vital for maintaining the sustainability of the watershed function (Hu et al. 2022; Pinto-Ramos et al. 2022; Falk et al. 2022; Li et al. 2017). Previous research on those matters found that the higher the diversity and density of vegetation, the higher the soil's ability to reduce erosion and maintain soil fertility, increasing the land's ability to maintain stable land cover (Borrelli et al. 2017). More studies corresponding with vegetation and the potential vulnerability of land cover for erosion risk found that vegetation density and diversity improve a land's ability to reduce erosion risk, which in turn helps maintain stable land cover (Tang et al. 2021; Chen and Zhang 2022; Beniaich et al. 2023; Francke et al. 2022; Kosmalla et al. 2022; Masroor et al. 2022). Thus, the vegetation role can be useful in interpreting land cover resilience conditions to observe potential land disasters. That is because vegetation is an important land cover component, which provides clues about the ecosystem's overall condition.

The vegetation existence that indicates the presence of LC can be observed using optical-based satellite imagery (Xu et al. 2023; Bobrowski et al. 2023; Mutanga et al. 2023). Previous research shows several important findings, namely: a positive correlation between the spectral vegetation index and the trend of changes in the vegetation index caused by the dynamics of climate change and the characteristics of drought risk (Praetyo et al. 2019), the extreme climate and vegetation dynamics measured on a monthly scale in the Central Asian region affect vegetation growth at different growth periods compared to on an annual scale (Luo et al. 2020), the process of changing vegetation distribution patterns are related to the frequency and magnitude of rainfall, as well as vegetation types in utilizing soil moisture levels (Eigentler and Sherratt 2020).

Therefore, this study is intended to combine optical-satellite map observation interpretation techniques based on monitoring temporal and statistical spatial patterns with field observations by measuring community readiness and the connection to the vegetation existence. With its wealth of vegetation and biological diversity, Indonesia offers the potential for a wide range of studies on this subject (Budy 2017).

This study aims to observe vegetation resilience by monitoring the vegetation cover affected by anthropogenic activities (e.g., decrease in farming, increase in housing, increase in hillside population) (Liu et al. 2021). The study's novelty is discovering the relationship between the dominant spatial land use pattern, the inhabitants' distribution, and the vegetation indices pattern. Therefore, research is tested in areas with complex ecological and social problems with great dynamic changes to achieve this goal. Garang Watershed is an example of a community-based vegetation management model. This watershed greatly influences the coastal city, Kendal District and Semarang City of Central Java Province, Indonesia which runs from Mount Ungaran to the northernmost coastal region on the edge of the Java Sea.

MATERIALS AND METHODS

Study area

Semarang City is located on the North Coast of the Island of Java, Indonesia, and covers an area of 373.70 km². It is bordered by Kendal District in the West, Demak District in the East, Semarang District in the South, and the Java Sea with a coastline of 13.6 km in length in the North. Semarang City was a shallow seabed covered by relatively thick sedimentary layers during the Miocene and Pleistocene. Therefore, Semarang and the surrounding area have three distinct rock types: volcanic rocks, sedimentary rocks derived from the sea, and weathered alluvial deposits from upstream areas. The Garang Watershed stretches from Mount Ungaran to the downstream area in Semarang City, with three tributaries: the Kripik River, Kreo River, and Garang River (Figure 1). The catchment areas of Garang River, Kripik River, and Kreo River, respectively, reach 204 km², 93.4 km², and 70 km².

This study divides the Garang Watershed area into three subsections based on its topography and slopes: upstream, midstream, and downstream. These sub-district areas were delineated to disseminate a proportional random-based questionnaire representing each sub-district (Figure 1 (*right*) and Table 1).

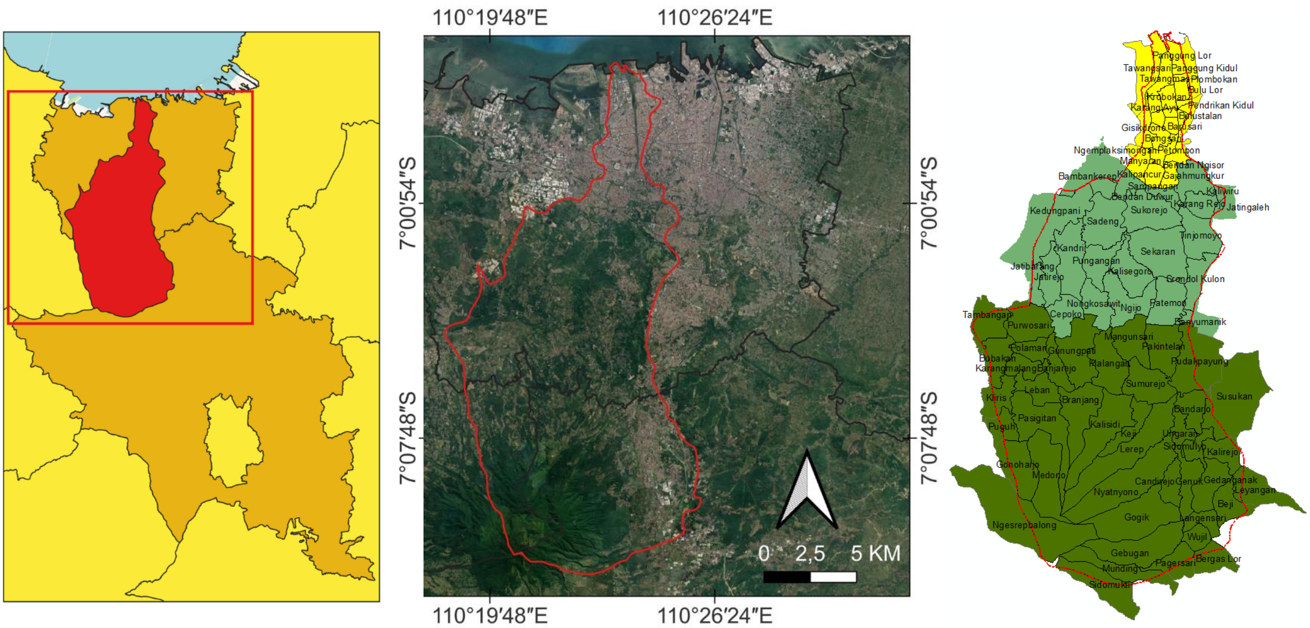

Figure 1. Location map of Garang Watershed basin, Semarang, Indonesia (*left*). Division of the Garang Watershed area and village names (*right*)

Table 1. 87 Villages in Garang Watershed, Semarang, Indonesia

Watershed	District	Village
Upstream	Kendal (District)	Ngesrepbalong, Gonoharjo, Medono, Pasigitan, Puguh, Kliris, Banjarejo, Leban.
	Semarang (District)	Beji, Bergas Lor, Branjang, Candirejo, Gebugan, Gedanganak, Genuk, Gogik, Kalirejo, Kalisidi, Keji, Langensari, Lerep, Leyangan, Munding, Nyatnyono, Pagersari, Sidomukti, Sidomulyo, Susukan, Ungaran, Wujil, Bandarjo.
	Semarang (City)	Bubakan, Karangmalang, Polaman, Purwosari, Tambangan, Gunungpati, Plalangan, Sumurejo, Pudakpayung, Pakintelan, Mangunsari.
Middlestream	Semarang (City)	Banyumanik, Patemon, Ngijo, Nongkosawit, Cepoko, Jatirejo, Jatibarang, Kedungpane, Kandri, Pungangan, Kalisegoro, Srondol Kulon, Tinjomoyo, Sekaran, Sukorejo, Sadeng, Bambankerep, Kalipancur, Jatingaleh, Kaliwiru, Bendan Duwur, Gajahmungkur, Karang Rejo.
Downstream	Semarang (City)	Bendan Ngisor, Petompon, Sampangan, Bojongsalaman, Bongsari, Cabean, Gisikdrono, Karang Ayu, Krobokan, Manyaran, Ngemplaksimongan, Salamanmloyo, Tawangmas, Tawangsari, Barusari, Bulustalan, Pindrikan Kidul, Pindrikan Lor, Bulu Lor, Panggung Kidul, Panggung Lor, Plombokan.

Procedures

Spatial-temporal analysis of satellite imageries for vegetation indices

The method used was an interpretation analysis of spatial-temporal satellite imagery, Landsat 8 OLI (Table 2). The source of the optical satellite images from 2015 to 2021 was downloaded from the United States Geological Survey (USGS) website. Satellite data from USGS has been widely used in research related to vegetation carried out by previous researchers (Ardiansyah et al. 2018; Robinson et al. 2017; Orellana-Alvear et al. 2020; Prodromou et al. 2021; Fu et al. 2022; Prasetyo et al. 2020). A vegetation analysis using remote sensing imagery was performed based on leaf surface indicators and canopies, which were easily extracted and observed from the satellite imagery. The vegetation index was the value of the quantitative measurement results of the vegetation canopy in receiving and reflecting the light spectrum. That was interpreted as a spectral characteristic of vegetation, both from the infrared (IR) spectrum and the near-infrared (NIR) spectrum (Figure 2).

In this study, vegetation indices were used to determine the existence of vegetation to encounter climate change in tropical regions in the dry and wet seasons. Generally, there is a recovery time from the dry to the wet season on the health of vegetation level; therefore, this study used the Normalized Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI) (Jarocinska and Zagajewski 2009; Araujo et al. 2000; Rodríguez-Moreno and Bullock 2014) using QGIS 2.18.

NDVI has been applied to various studies in agriculture, forestry, ecology, biodiversity (Sutomo and Wahab 2019), habitat modeling, species migration, earth system processes (nutrient cycle, primary productivity, evapotranspiration), and even economic, social, and medical sciences. An NDVI value close to 1 indicates very dense vegetation, and a value close to 0 indicates vacant land or very sparse vegetation. In addition, a negative NDVI value indicates a body of water or an urban area.

SAVI was developed to reduce the noise influence from the soil surface due to vegetation cover changes. The algorithm used in SAVI was created to minimize the influence of the soil background reflected and recorded in satellite imagery so that the vegetation canopy is independent of soil reflectance. Based on this understanding, SAVI can be applied to studies that indicate vegetation with a low canopy (Huete 1988; Ihlen 2019). In interpreting satellite imagery, the NDVI and SAVI algorithms use the formulas shown in Table 3 (Vermote et al. 2016; Ihlen 2019).

The existence of vegetation as a representation of ecological value is the primary concern in this research and was studied through the interpretation of optical-based satellite imagery. First, vegetation monitoring was carried out based on the existence of vegetation represented by the Normalized Difference Vegetation Index (NDVI) for high-canopy vegetation and the Soil-Adjusted Vegetation Index (SAVI) for low-canopy vegetation. The existence of vegetation monitored in the dry and wet seasons is then analyzed to find the total resilience value by measuring the trendline angle (total α) value with the scheme presented in Figure 3.

Furthermore, Climate Action (CA) was formulated concerning the human responsibility in the form of real climate action to respect and protect green space, as the human factor social values for nurturing vegetation. The results were validated by linking the analysis of satellite imagery interpretation with a field investigation. That included disseminating a random-based questionnaire to residents in the watershed area to obtain information about their social values, knowledge, attitudes, responses, and local village institutions' role in caring for vegetation. These findings will be used later in developing a causal loop scenario in preparing community participation-based climate action.

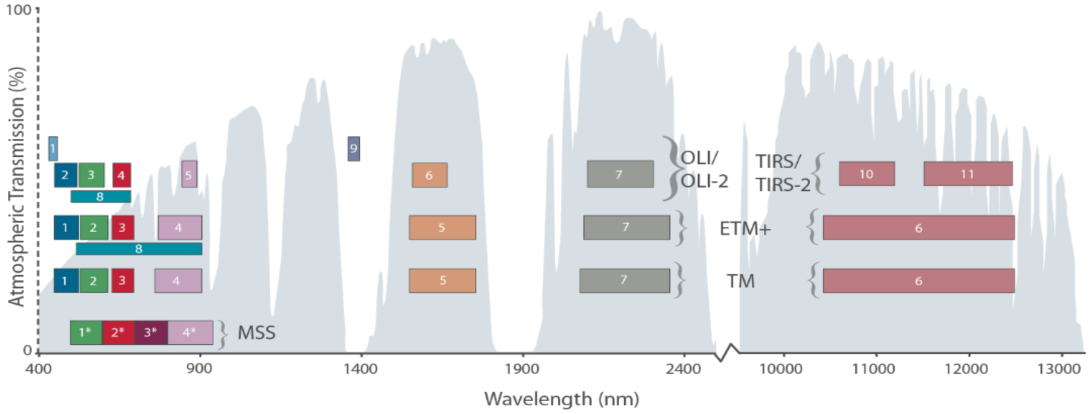

Figure 2. Spectral bands and wavelengths for Landsat sensors (Ihlen 2019)

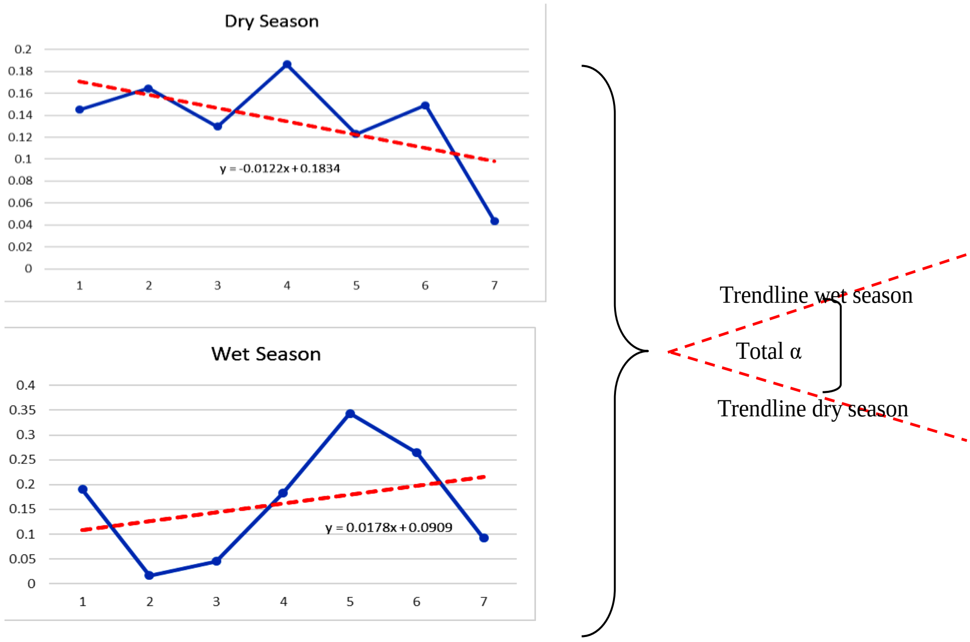

Figure 3. Total trendline angle of change in vegetation index (Total α = trendline wet angle+trendline dry angle)

Table 2. List of the used files from Landsat 8 OLI

Years	Season	Files
2015	Wet season	LC08_L1TP_120065_20150105_20170412_01_T1.tar
	Dry season	LC08_L1TP_120065_20150918_20170404_01_T1.tar
2016	Wet season	LC08_L1TP_120065_20160209_20170330_01_T1.tar
	Dry season	LC08_L1TP_120065_20160904_20170321_01_T1.tar
2017	Wet season	LC08_L1TP_120065_20170211_20170217_01_T1.tar
	Dry season	LC08_L1TP_120065_20170907_20170926_01_T1.tar
2018	Wet season	LC08_L1TP_120065_20180302_20180308_01_T1.tar
	Dry season	LC08_L1TP_120065_20180926_20181009_01_T1.tar
2019	Wet season	LC08_L1TP_120065_20190217_20190222_01_T1.tar
	Dry season	LC08_L1TP_120065_20190929_20191017_01_T2.tar
2020	Wet season	LC08_L1TP_120065_20200510_20200820_02_T1.tar
	Dry season	LC08_L1TP_120065_20200830_20200906_02_T1.tar
2021	Wet season	LC08_L2SP_120065_20210121_20210307_02_T1
	Dry season	LC08_L2SP_120065_20210902_20210909_02_T1

Table 3. Algorithms of NDVI and SAVI from Landsat 8 OLI

NDVI	(Band 5 - Band 4)/(Band 5 + Band 4)
SAVI	((Band 5 - Band 4)/(Band 5 + Band 4 + 0.5))*(1.5)

Spatial-temporal analysis of satellite imageries for dominant land use change

Optical satellite images covering 2002 to 2022 were freely downloaded from Google Earth. The Google Earth satellite images were processed to determine Land Use Change (LUC) using supervised classification techniques with QGIS 2.18. Therefore, downloading the imagery map within the Garang watershed area divides it into 83 reference points to obtain a high-resolution from Google Earth (Figure 4, Table 4). Furthermore, the imagery map is carried out by a georeferencing process to be combined into one high-resolution image map in one unit of the Garang watershed area, which is ready to be interpreted by its LUC with supervised classification techniques (Sampurno and Thoriq 2016; Indrawati and Cahyono 2018).

Spatial-temporal analysis of inhabitant change

The inhabitants change from 2015 to 2020 were obtained from the Central Statistics Agency in Kendal District (https://kendalkab.bps.go.id), Semarang District (https://semarangkab.bps.go.id), and Semarang City (https://semarangkota.bps.go.id), which were published in 2021. However, the inhabitant's data by villager level in the three regions in 2021 (published in 2022) has not been obtained. That was because it is still waiting for the official publication from the regional authorities.

Analysis of community readiness for climate action

The community's readiness and psychological condition are important factors to drive community participation in environmental management. Readiness is defined as the ability to put oneself in a state of being prepared to start a movement or series of actions (Table 5) (Conahan and Kyere 2015; APA 2022).

This study elaborates on four measurement variables: attitudes, knowledge, responses, and the role of external institutions. These four variables represent community readiness up to the 6th level (Tables 6, 7, 8, and 9).

Testing was conducted by distributing a proportional random questionnaire (Taherdoost 2018) divided into 87 village areas. The weighting results on social values were then observed in a spatial pattern using spatial autocorrelation analysis. At this stage, the social values were observed according to the distribution of the three locations, namely upstream, midstream, and downstream sub-areas, along with Moran's index values representing these patterns (Anselin 2019; Ihlen 2019; Banerjee et al. 2015). These data will subsequently be used to compile space-scale climate action steps.

The linkage analysis of the community readiness levels in climate action with vegetation index change trends

The connection between community readiness and changes in vegetation indices was tested using Smart-PLS 3 for Partial Least Square (PLS) analysis. The linkage model was tested with the following two schematics (Figure 5).

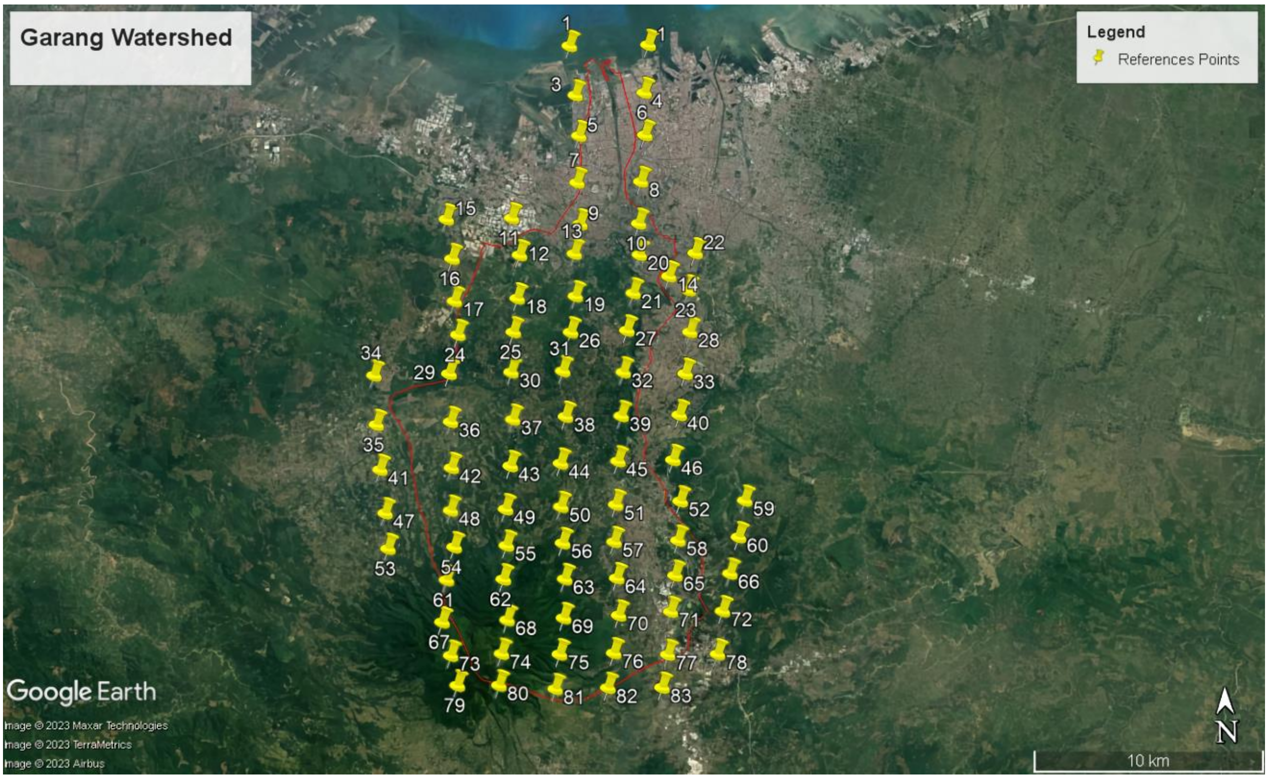

Figure 4. Locations of reference points to download Google Earth imagery map 2002-2022

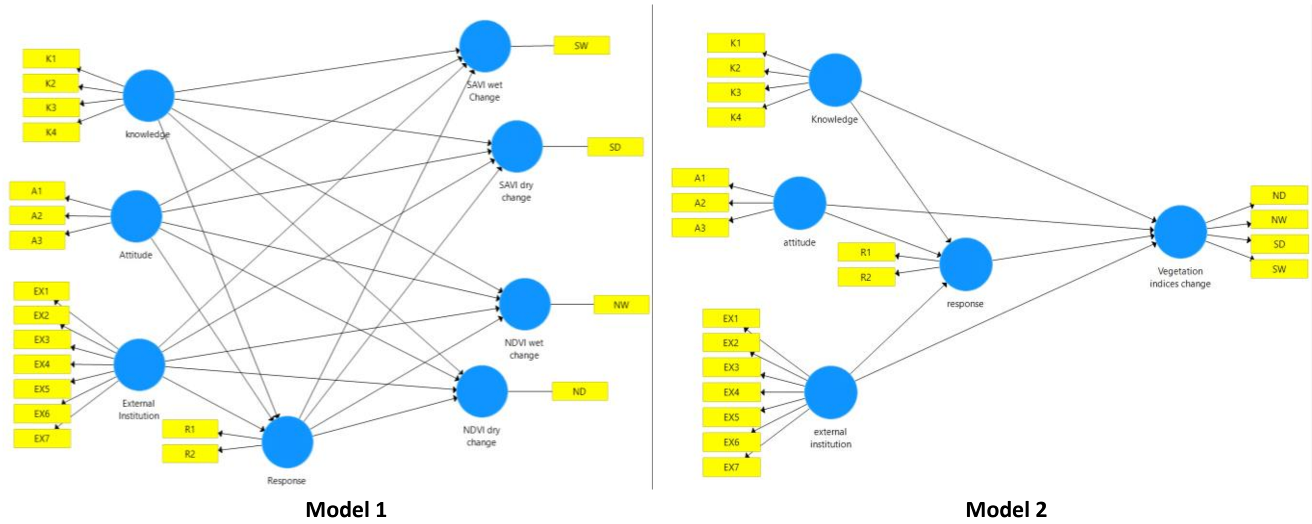

Figure 5. Community Readiness Linkage Model with Vegetation Index Changes

Table 4. List of reference points on Google Earth

Points	latitude	longitude	Points	latitude	longitude	Points	latitude	longitude
1	-6.945847°	110.381777°	33	-7.075122°	110.424715°	65	-7.154053°	110.419099°
2	-6.946100°	110.412785°	34	-7.073341°	110.302220°	66	-7.153706°	110.440724°
3	-6.965245°	110.383720°	35	-7.092647°	110.302708°	67	-7.170454°	110.327003°
4	-6.964798°	110.410839°	36	-7.092115°	110.331987°	68	-7.170132°	110.352630°
5	-6.981152°	110.384783°	37	-7.091688°	110.356491°	69	-7.169801°	110.374890°
6	-6.981396°	110.410783°	38	-7.090979°	110.377275°	70	-7.169189°	110.396600°
7	-6.999511°	110.383681°	39	-7.091171°	110.399205°	71	-7.168192°	110.417070°
8	-6.999631°	110.408798°	40	-7.091226°	110.422036°	72	-7.168380°	110.437512°
9	-7.015742°	110.384520°	41	-7.110285°	110.303805°	73	-7.183629°	110.330130°
10	-7.015984°	110.407644°	42	-7.110122°	110.331947°	74	-7.183283°	110.350159°
11	-7.012839°	110.357664°	43	-7.109858°	110.355137°	75	-7.183950°	110.372979°
12	-7.027366°	110.360463°	44	-7.109257°	110.374941°	76	-7.183947°	110.394363°
13	-7.027309°	110.382027°	45	-7.108850°	110.397585°	77	-7.184993°	110.415581°
14	-7.036887°	110.419093°	46	-7.108760°	110.419214°	78	-7.185178°	110.435205°
15	-7.012736°	110.331960°	47	-7.127347°	110.305456°	79	-7.195368°	110.332475°
16	-7.028297°	110.333896°	48	-7.126827°	110.331281°	80	-7.195645°	110.348877°
17	-7.044894°	110.334472°	49	-7.126697°	110.352935°	81	-7.197521°	110.370989°
18	-7.044293°	110.359212°	50	-7.126211°	110.374716°	82	-7.197504°	110.391751°
19	-7.043916°	110.382108°	51	-7.125841°	110.396311°	83	-7.197822°	110.413064°
20	-7.028228°	110.407659°	52	-7.125009°	110.421725°			
21	-7.043185°	110.404933°	53	-7.141272°	110.306284°			
22	-7.028024°	110.429600°	54	-7.141172°	110.332376°			
23	-7.042507°	110.426694°	55	-7.140962°	110.352957°			
24	-7.058103°	110.335572°	56	-7.140435°	110.375111°			
25	-7.057469°	110.357417°	57	-7.140412°	110.395375°			
26	-7.057994°	110.379975°	58	-7.140349°	110.420524°			
27	-7.057723°	110.402128°	59	-7.125251°	110.447128°			
28	-7.058863°	110.426903°	60	-7.139529°	110.444401°			
29	-7.073255°	110.331782°	61	-7.153978°	110.329079°			
30	-7.073175°	110.356212°	62	-7.154150°	110.351485°			
31	-7.073131°	110.376559°	63	-7.154539°	110.375665°			
32	-7.074059°	110.400373°	64	-7.154606°	110.396139°			

Table 5. Community readiness level classification

Level	Description
No Awareness	The community or leaders need to be made aware of the problem
Denial/Resistant	The lack of public awareness of the issue they are facing
Vaque Awareness	The lack of general knowledge of the local potential they have
Preparation	The community begins to organize themselves
Preplanning	The community begins to realize the problems that occur
Initiation	The local leader figures can convey information
Stabilization	Monitoring the community's socioeconomic dynamics has begun to be carried out
Confirmation/Expansion	The development of activities has involved the community
Professionalization	The community begins to evaluate and modify the program

Table 6. List of questions for levels 1 and 2 associated with attitude

Code	Question for attitude	Answer	Weight
A1	Do you feel the air temperature getting hot recently?	Yes	1
		Do not care	0
		No	-1
A2	Does the existence of various trees around you need to be preserved by caring for them alone and together?	Yes	1
		Do not care	0
		No	-1
A3	Do you participate in preserving and planting trees in your environment?	Yes	1
		Do not care	0
		No	-1

Table 7. List of questions for levels 3 and 4 associated with knowledge

Code	Question for knowledge	Answer	Weight
K1	We need to preserve trees in our environment because trees can make the air fresher and the temperature relaxed.	Agree	2
		Abstain	1
		Disagree	-1
K2	Does the presence of various trees around you mean anything for efforts to prevent flooding?	Yes	1
		Do not know	0
		No	-1
K3	Do you know your village is included in the Garang Watershed?	Yes	1
		Do not know	0
		No	-1
K4	What are the benefits for you regarding the Existence of the Garang Watershed?	Right	1
		Do not know	0
		Wrong	-1

Table 8. List of questions for level 5th associated with response

Code	Question for response	Answer	Weight
R1	Do you plant in your house or surrounding?	Yes always	2
		Yes sometimes	1
		No	-1
R2	What kind of plants are you planting?	High Canopy	2
		Low Canopy	1

Table 9. List of questions for level 6th associated with external institution roles

Code	Question for external institution roles	Answer	Weight
EX1	Is there a movement in your village to plant trees from the organization or the local government?	Yes	3
		Do not care	2
		No	1
EX2	At the organization, are there regular meetings to discuss the movement?	Yes	3
		Do not care	2
		No	1
EX3	Is there a role for religious leaders in managing natural resources, especially trees?	Yes	3
		Do not care	2
		No	1
EX4	Is there a role of traditional figures in managing the natural resources, especially trees, in your village?	Yes	3
		Do not care	2
		No	1
EX5	Is there a role for the government in managing natural resources, especially trees?	Yes	3
		Do not care	2
		No	1
EX6	In managing trees in and around the village, do you ask for consideration from religious, customary, community, and government leaders?	Yes	3
		Do not care	2
		No	1
EX7	Is there a movement to plant trees in your residence?	Yes	3
		Do not care	2
		No	1

RESULTS AND DISCUSSION

Values of vegetation indices and linear trend change 2015-2021

The complete data processing steps for SAVI and NDVI in the dry and wet seasons and the changes in the measured vegetation index values with the slope angle values of the trend line changes (α) for 2015-2021 are presented in http://repository.usm.ac.id/files/document/C015/20230216 014212-Appendix-A.docx. In addition, a summary of the results of the processing vegetation index is presented in Table 10.

This data shows vegetation degradation with a number $(NDVI\text{-}SAVI)_{wet\text{-}dry}$ of 0.173571 in the Semarang District. The region also showed the lowest level of vegetation resilience of 1.116204392 in SAVI and 1.339069368 in NDVI compared to other upstream areas.

Global Moran's Index (GMI) for residential, inhabitant, and vegetation indices

Residential is the most dominant type of land use in the Garang watershed, shown in Figures 6, 7, 8, and 9. Therefore, the study's hypothesis, residential change, will align with the dynamics of inhabitant changes. For this reason, inhabitants' spatial pattern changes are also calculated.

The results of the valuation analysis of residential, population, and vegetation index distribution patterns with GMI values are presented in Tables 11, 12, 13, and 14. In addition, the relationship between vegetation indices, residential, and inhabitant distribution was determined using a multi-correlation analysis (Table 15). The multi-correlation analysis summary shows that changes in the NDVI and SAVI spatial patterns are strongly related to changes in the spatial patterns of inhabitant and residential indices, which are indicated by values R^2 = 0.623212 for NDVI with F_{count} = 3.308025 > F_{table} = 0.141969, and R^2 = 0.309425 for SAVI, with F_{count} = 0.896139 > F_{table} = 0.476893.

The relationship between vegetation index and residential as a representation of dominant land use and the number of inhabitants is significant for NDVI and SAVI in the dry season. This relationship is in the form of spatial patterns represented by GMI values. Although these results show the relationship of spatial patterns between these variables, looking at the vegetation index in the dry season seems more appropriate if it is associated with social dynamics that become human characters in the inhabitant. In the wet season, the connectedness of spatial patterns shows a less significant association. This may be due to other factors, such as climate and soil fertility, that have a greater influence than the impact of anthropogenic activities. In some cases, the influence of human activities can be more significant than the influence of climate, especially if those human activities are carried out uncontrollably and in large quantities. However, the influence of climate remains an important factor in damaging vegetation in watersheds, especially over long periods, and climatic conditions continue to change dramatically.

Values of community readiness

The study elaborates on four measurement variables: attitudes, knowledge, responses, and the role of external institutions. The results of the GMI (Figures 10 to 13) show a minimum value of 0.099 and a maximum of 0.359. This shows that the spatial distribution pattern of social variables is a dispersion on almost all variables. There is even one "scatter" pattern in the knowledge variable of -0.036. Therefore, it has been concluded that the spatial pattern and GMI scores of community readiness shows "disperse" across all scores, knowledge, attitudes, responses, and the role of external institutions. The results of their weighting can be seen at: http://repository.usm.ac.id/files/document/C015/20230216014416-Appendix-B.docx.

Furthermore, the summary of the community readiness values without spatial pattern consideration (Table 16) shows that community readiness in the upstream area, specifically in the Kendal District, is in the best position with a value of 6.627976. Conversely, the lowest value of 4.257092 is found in the upstream area, in the Semarang District.

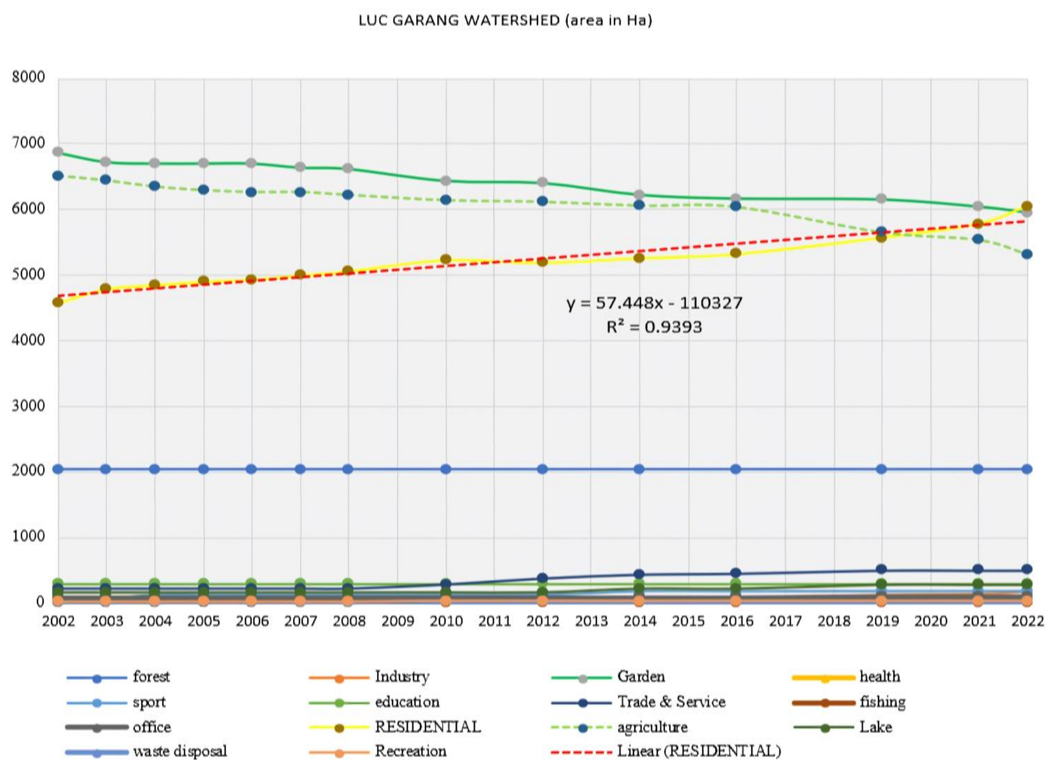

Figure 6. The high residential changes of Garang Watershed from 2002 to 2022

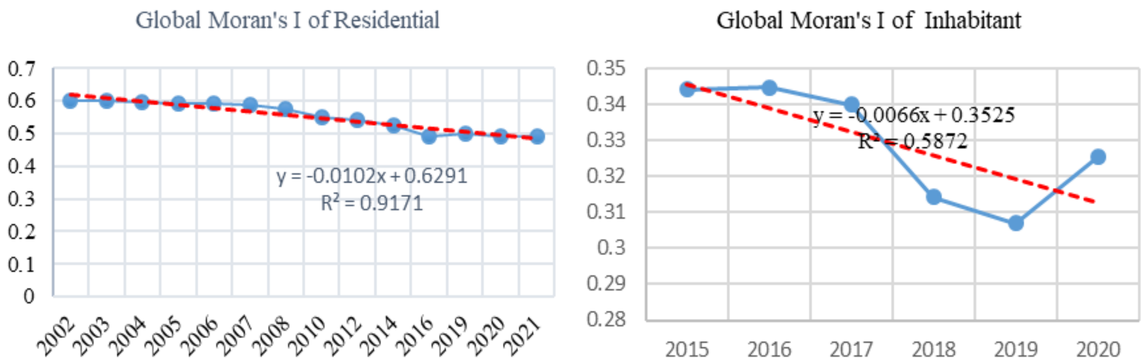

Figure 7. Linear trend of GMI residential and inhabitant indices

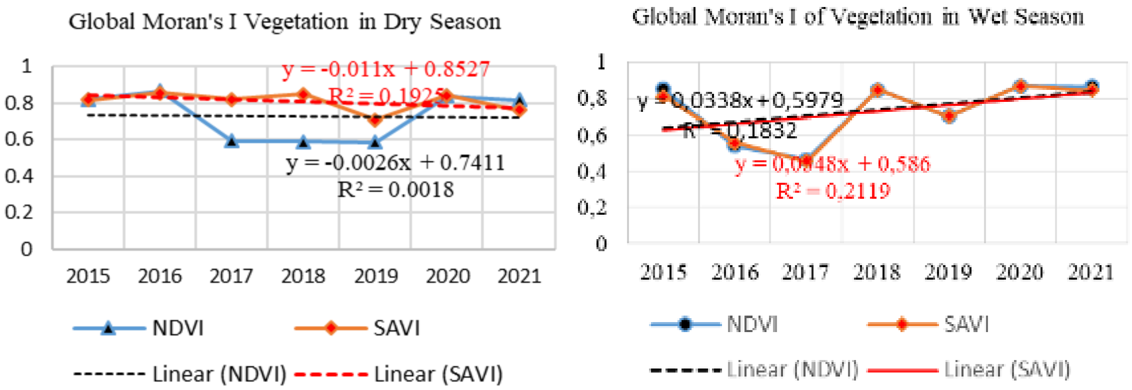

Figure 8. Linear trend of GMI vegetation indices

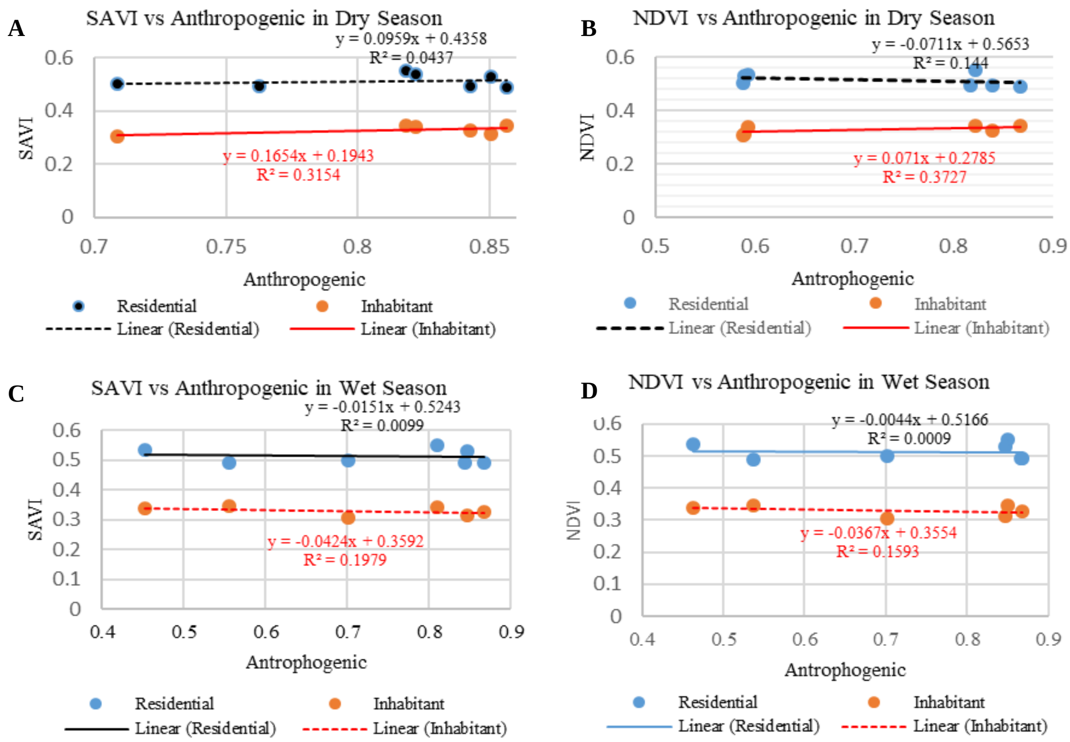

Figure 9. Linear correlation between GMI's SAVI and NDVI with GMI's anthropogenic activities

The relationship between community readiness and the change in vegetation indices

The results of testing the relationship between the value of community readiness and the trend of changes in vegetation index in the last five years in the Garang watershed show a significant influence. Model 1 shows that the external role of institutions significantly influences community response to maintaining vegetation, with R^2 = 0.565 in Model 1 and R^2 = 0.567 in Model 2 (Figure 14). Meanwhile, the levels of knowledge and attitudes of the community significantly affect the changes in vegetation indices, especially in the wet season, with R^2 = 0.207 for SAVI and 0.232 for NDVI (Model 1 in Figure 14). Community attitudes also significantly affect the changes in vegetation indices in Model 2 with a value of R^2 = 0.281.

Table 10. Values of vegetation indices and linear trend change 2015-2021

		District	**$SAVI_{Dry}$**	**$SAVI_{Wet}$**	**$NDVI_{Dry}$**	**$NDVI_{Wet}$**	**$(NDVI-SAVI)_{Dry}$**	**$(NDVI-SAVI)_{Wet}$**	**$(NDVI-SAVI)_{Wet-Dry}$**
The values of vegetation indices/5 years	Up Stream	Kendal District	0.361492	0.262299	0.377409	0.509418	0.01591675	0.247118792	0.231202
		Semarang District	0.332382	0.269011	0.349415	0.459615	0.017032335	0.19060346	**0.173571**
		Semarang City	0.351493	0.296236	0.373518	0.499256	0.022024871	0.203019239	0.180994
	Middle Stream	Semarang City	0.30656	0.258018	0.330949	0.443385	0.024389387	0.185367143	0.160978
	Down Stream	Semarang City	0.144003	0.145324	0.198302	0.219981	0.054299137	0.07465731	0.020358
The values of the trendline's slope	Up Stream	Kendal District	-0.96238	0.741894	1.787581		-1.12281	1.704269746	1.864705567
		Semarang District	-0.58837	0.527833	1.200811		-0.81124	**1.116204392**	**1.339069368**
		Semarang City	-0.74686	0.799976	1.371084		-0.94632	1.546831755	1.746295949
	Middle Stream	Semarang City	-0.73832	0.609283	1.436151		-1.13327	1.347604961	1.742556642
	Down Stream	Semarang City	-0.80755	0.08255	0.377591		-0.85649	0.890104258	0.939044256

Table 11. Global Moran's Index (GMI) of residential

Year	**GMI statistics**	**Variance**	**SD**	**p-value**
2002	0.59986445	0.00405074	9.6078	<2.2e-16
2003	0.60148021	0.00405074	9.6332	<2.2e-16
2004	0.59514803	0.00405074	9.5337	<2.2e-16
2005	0.59277910	0.00405074	9.4965	<2.2e-16
2006	0.58982889	0.00405074	9.4501	<2.2e-16
2007	0.58779820	0.00405074	9.4182	<2.2e-16
2008	0.57675493	0.00405074	9.2447	<2.2e-16
2009	NA	NA	NA	NA
2010	0.54996237	0.00405074	8.8237	<2.2e-16
2011	NA	NA	NA	NA
2012	0.54078394	0.00405074	8.6795	<2.2e-16
2013	NA	NA	NA	NA
2014	0.52560881	0.00405074	8.4411	<2.2e-16
2015	NA	NA	NA	NA
2016	0.49062723	0.00405074	7.8915	<1.493e-15
2017	NA	NA	NA	NA
2018	NA	NA	NA	NA
2019	0.50145732	0.00405074	8.0616	<3.765e-16
2020	0.49253668	0.00408508	7.8881	<3.078e-15
2021	0.49272283	0.00408494	7.8911	<2.994e-15

Table 12. Global Moran's Index (GMI) of inhabitants

Year	**GMI Statistics**	**Variance**	**SD**	**p-value**
2015	0.34415038	0.00400088	5.6247	1.858e-08
2016	0.34471310	0.00400963	5.6275	1.828e-08
2017	0.33996513	0.00399079	5.5656	2.613e-08
2018	0.31437432	0.00398415	5.2230	1.761e-07
2019	0.30702618	0.00398415	5.0484	4.456e-07
2020	0.32556704	0.00395679	5.3606	8.297e-08
2021	NA	NA	NA	NA

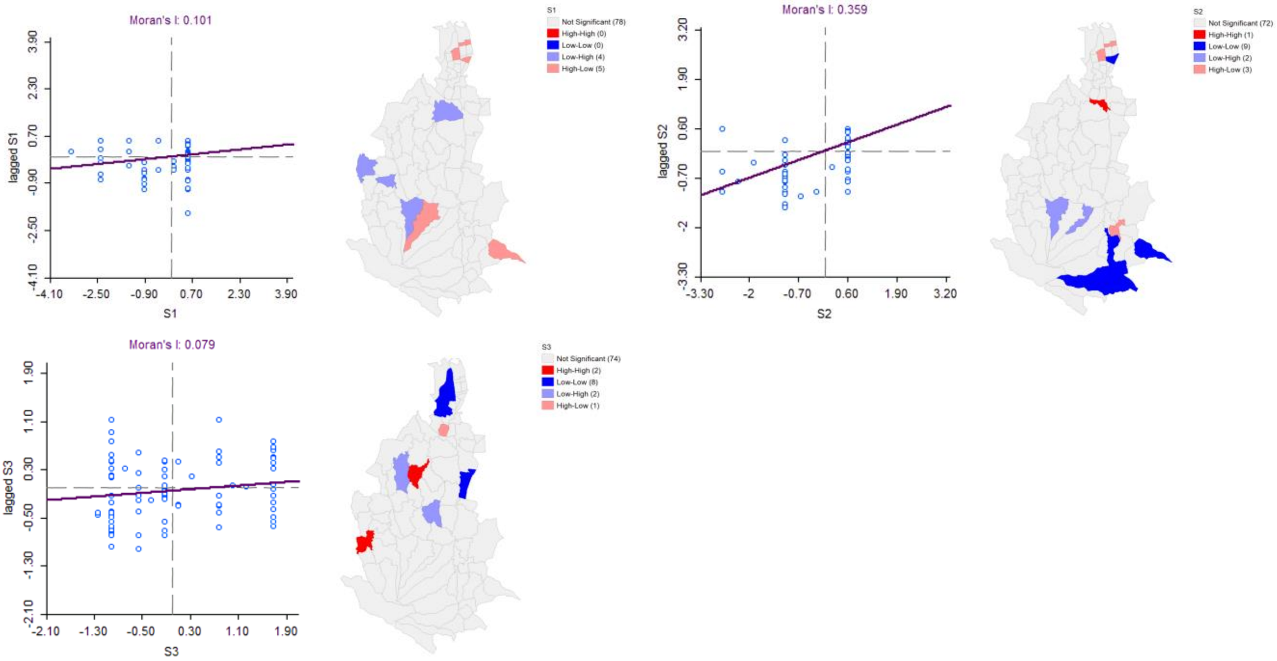

Figure 10. Spatial autocorrelation of attitude scores

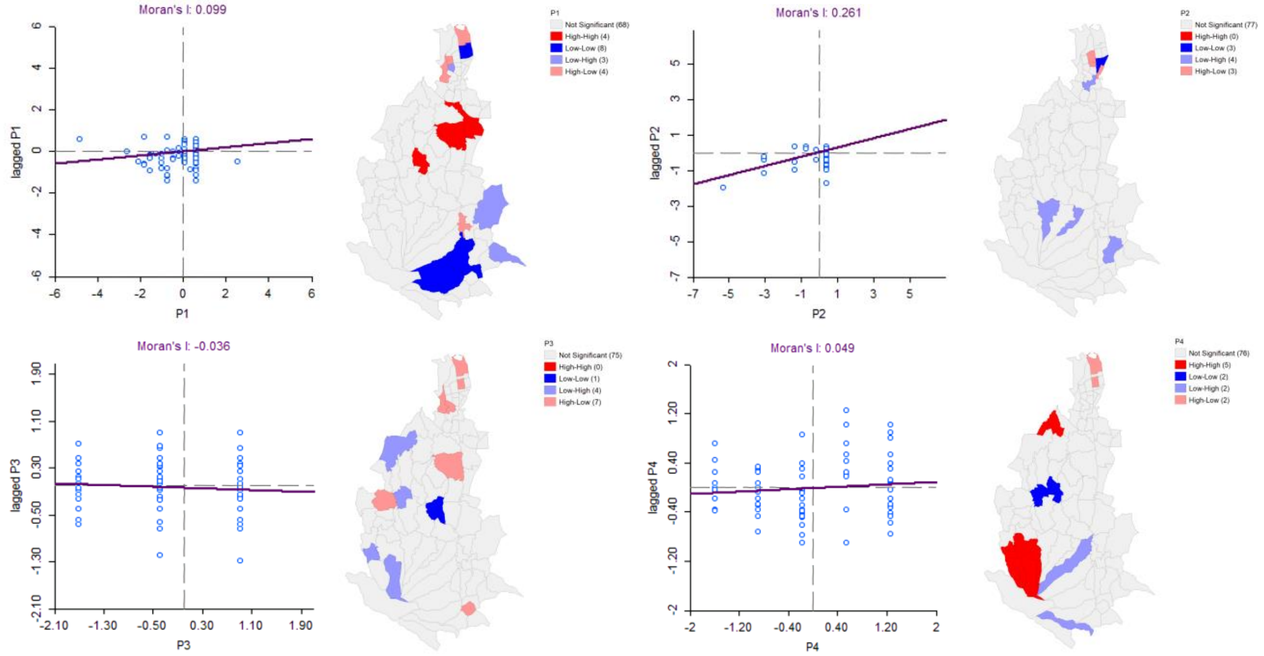

Figure 11. Spatial autocorrelation of knowledge scores

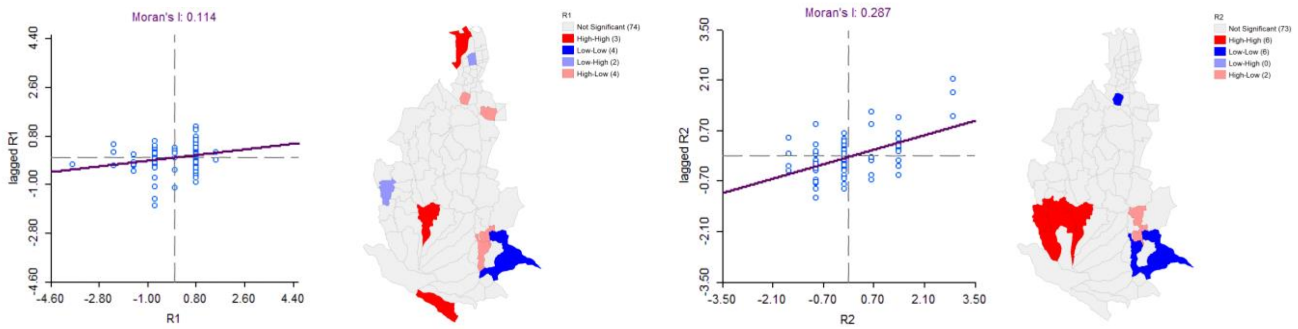

Figure 12. Spatial autocorrelation of response scores

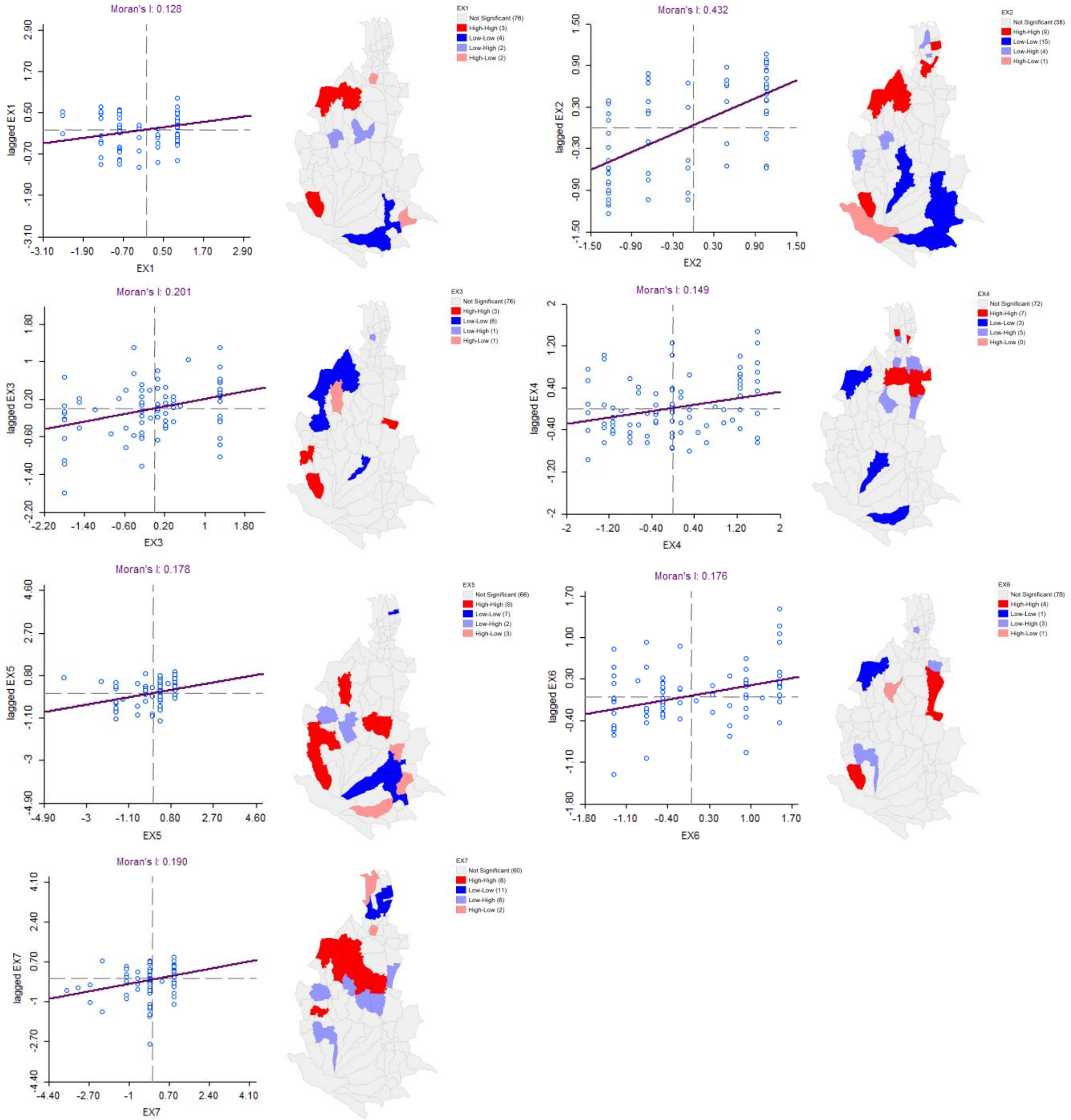

Figure 13. Spatial autocorrelation of the role of external institution scores

Table 13. Global Moran's Index (GMI) of NDVI

Year	GMI statistics	Variance	SD	p-value
NDVI Dry season				
2015	0.82135164	0.00440019	12.557	<2.2e-16
2016	0.86667256	0.00410015	13.716	<2.2e-16
2017	0.59277910	0.00409921	13.219	<2.2e-16
2018	0.58982889	0.00410733	13.454	<2.2e-16
2019	0.58779820	0.00411015	10.645	<2.2e-16
2020	0.83925191	0.00410364	13.283	<2.2e-16
2021	0.81685956	0.00410045	12.938	<2.2e-16
NDVI Wet season				
2015	0.8501648	0.00410521	13.45	<2.2e-16
2016	0.5372418	0.00404635	8.6285	<2.2e-16
2017	0.4627575	0.00393216	7.5651	<2.2e-16
2018	0.8472731	0.00408187	13.444	<2.2e-16
2019	0.7014147	0.00409408	11.144	<2.2e-16
2020	0.8673953	0.00409830	13.731	<2.2e-16
2021	0.8662576	0.00409937	13.711	<2.2e-16

Table 14. Global Moran's Index (GMI) of SAVI

Year	GMI statistics	Variance	SD	p-value
SAVI Dry season				
2015	0.8181267	0.0041034	12.953	<2.2e-16
2016	0.8563151	0.0041060	13.545	<2.2e-16
2017	0.8221164	0.0040395	13.015	<2.2e-16
2018	0.8506387	0.0041073	13.454	<2.2e-16
2019	0.7088667	0.0041089	13.240	<2.2e-16
2020	0.8425509	0.0041093	13.325	<2.2e-16
2021	0.7625769	0.0041106	12.076	<2.2e-16
SAVI Wet season				
2015	0.8101381	0.0041060	12.824	<2.2e-16
2016	0.5548164	0.0040579	8.8922	<2.2e-16
2017	0.4525699	0.0040059	7.3342	<2.2e-16
2018	0.8472736	0.0040819	13.444	<2.2e-16
2019	0.7014153	0.0040941	11.144	<2.2e-16
2020	0.8671412	0.0041046	13.721	<2.2e-16
2021	0.8440577	0.0040951	13.372	<2.2e-16

Table 16. The values of community readiness in Garang Watershed

			Knowledge	Attitudes	Response	Ex. inst.	Accumulation
Community readiness values	Upstream	Kendal District	1.05625	0.808333	1.96875	2.794643	6.627976
		Semarang District	0.818478	0.572464	1.01087	1.85528	4.257092
		Semarang City	0.618182	0.793939	1.318182	2.161039	4.891342
	Mid stream	Semarang City	0.817391	0.753623	1.25	2.287026	5.108040
	Down stream	Semarang City	0.705682	0.562121	1.375	2.298052	4.940855

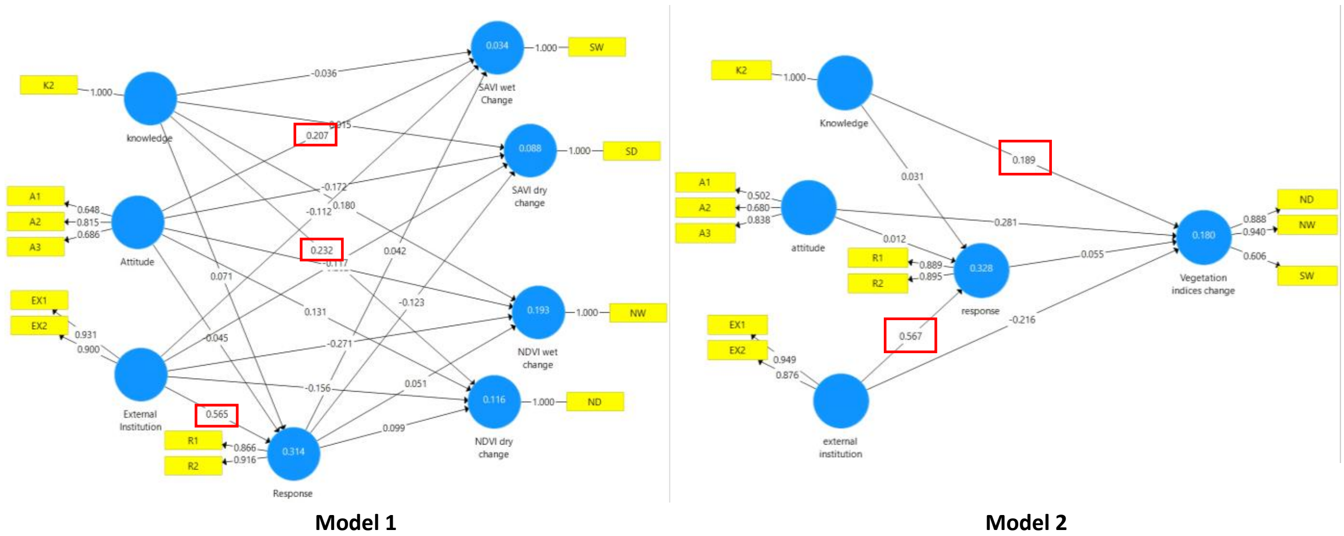

Figure 14. Degree of the relationship between community readiness and vegetation indices

Table 15. Resume results in multi-correlation analysis GMI's SAVI, NDVI with GMI's anthropogenic activities

Description	**Multiple R**	**R Square**	**Adjusted R Square**	**Standard Error**	**Regression ANOVA**					***Coefficients***		
					df	**SS**	**MS**	**F**	***Significance F***	**Intercept**	**Residential**	**Inhabitant**
NDVI Dry	0.789438	*0.623212*	0.434818	0.099547	2	0.065563	0.032781	*3.308025*	*0.141969*	0.214173	-3.12952	6.457788
SAVI Dry	0.55626	*0.309425*	-0.03586	0.055021	2	0.005426	0.002713	*0.896139*	*0.476893*	0.101544	0.120294	1.963223
NDVI Wet	0.415669	0.172781	-0.24083	0.190215	2	0.030229	0.015114	0.417739	0.684291	2.041773	0.645009	-4.98741
SAVI Wet	0.451013	0.203413	-0.19488	0.178679	2	0.03261	0.016305	0.51071	0.634552	2.283694	0.208291	-5.06525

Formula : NDVI = 0.214173-3.12952*Residential+6.457788*Inhabitant
Formula : SAVI = 0.101544+0.120294*Residential+1.963223*Inhabitant

Discussion

The change in vegetation indices

The results of monitoring changes in vegetation index values represented by SAVI and NDVI in the last five years show several important findings to be considered in managing watershed land cover. First, changes in vegetation index in watersheds are phenomena that occur in many other places, such as in the Serang Kulonprogo watershed (Setyawan et al. 2019), Bodri watershed, Cacaban watershed, Juwana watershed, Tuntang watershed, Pemali watershed, Kupang watershed, Solo watershed (Aryani et al. 2020).

However, in the Garang watershed, these values occur in upstream areas indicated by land use dynamics and population changes, namely in the Semarang District. Therefore, this requires more attention to maintain the existence of watersheds as a buffer for various ecosystem services such as water regulation services, clean water supply, biodiversity conservation, food and raw materials provision, erosion and sedimentation control, climate regulation, recreation and tourism. Furthermore, Semarang District, as part of the upstream Garang watershed, has a very strategic role, especially in controlling erosion and sedimentation, which is very dangerous for the downstream area in Semarang City.

The change of spatial pattern by GMI and LMI values

The Global Moran's Index (GMI) results for the distribution of inhabitants and residential areas indicate a tendency for population spread due to dispersion. The results show a linear index decline with a high confidence level of R^2 = 0.5872 for inhabitants and R^2 = 0.9171 for residential areas (Figure 7). However, the changing pattern indicated by the GMI value for vegetation indices does not show a significant value, even though there seems to be a tendency to change for a dispersed pattern (decrease in GMI value) in the dry season. There is a tendency to return to the cluster pattern (increase in GMI value) in the wet season (Figure 8). This finding shows that vegetation degradation has been indicated by changes in spatial patterns towards dispersion. This vegetation degradation is spatially correlated with the dynamics of changes in spatial patterns of anthropogenic activities represented by inhabitants.

In connection with the importance of maintaining vegetation resilience to climate change (Pinto-Ramos et al. 2022), the fragmentation of vegetation indices in the Garang Watershed requires attention. It can be said that the more fragmentation that occurs, the less likely that seeds can achieve climate resilience (Falk et al. 2022). In addition, the density of vegetation is affected more by "edge effects" such as increased light, dry air, and fire risk, creating conditions that jeopardize the sustainability of land cover in watersheds (Jha et al. 2019; Mirchooli et al. 2020).

Edge effect in the context of vegetation resilience refers to changes and influences along the boundary or edge of a habitat or ecosystem. For example, a forest habitat or agricultural land is cut or fragmented by human activities, such as road construction or settlements, the edge of a newly formed habitat. The impact is that along this edge, there is a change in that environmental conditions are different from the inside of the habitat (previous habitat). Some effects often occur in the edge effect include temperature, humidity, light intensity, wind, and plant species composition changes. For example, habitat edges tend to have higher temperatures, lower humidity, and more intense light exposure. These environmental conditions can affect the distribution and abundance of plant species and interactions between plants and animals.

Edge effects can also affect vegetation resilience. Plants growing at the edge of habitats may experience greater stress due to rapid and drastic changes in environmental conditions. As a result, they can become more vulnerable to disorders such as disease, pest infestation, or climate change. In addition, the edge effect can affect interactions between plants through increased competition or changes in insect pollination patterns. Therefore, it is very important to keep vegetation connected.

The relationship between the SAVI and NDVI indices and the inhabitant's index in the dry season is significantly high (Figures 9A and 9B). These findings show that inhabitant factors need to be considered in vegetation management. These inhabitant factors include the dynamic changes in spatial patterns, dynamic changes in numbers, and the social variables they contain, which need to be considered in vegetation management. The most significant social variables in the study area, Garang watershed, are the values of knowledge and attitude.

As well as research results elsewhere, namely in Malaysia (Mahat et al. 2020; Mahat et al. 2019), Qatar (Al-Nuaimi and Al-Ghamdi 2022), and Nigeria (Erhabor and Don 2016), social variables in the form of attitude and knowledge seem to be important social capital in shaping the character of society in maintaining ecosystems. However, in some of these studies, concrete valuations in quantitative values useful in estimating the strength of climate action have not been observed. Thus, the findings on the valuation of social value in the Garang watershed in numerical weights are the starting point for developing the formulated climate action scenarios in follow-up studies.

Spatial pattern of community readiness in Garang watershed

Generally, the spatial pattern of community readiness shows a dispersion pattern with GMI values ranging below 0.3 (Figures 10, 11, 12, and 13). That shows the watershed residents' readiness to respond to the presence of vegetation is weak, following previous studies (Conahan and Kyere 2015; APA 2022; Jones 2017). Therefore, the existence and resilience of vegetation should be supported by a spatial "*cluster*" pattern, especially in the upstream and midstream regions (Manfredo et al. 2021). In addition, this kind of spatial pattern requires more community participation encouragement in climate action to maintain vegetation resilience (Manfredo et al. 2017; Manfredo et al. 2020; Venghaus et al. 2022). Finally, community participation encouragement in the Garang Watershed is recommended to optimize the role of village institutions or NGOs, represented by R^2 = 0.565 in model 1 and R^2 = 0.567 in model 2 in Figure 14, for external institutions with community "*responses*" to climate action in vegetation care.

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