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Geospatial Approach in Predicting Radicalism Incidence in Peninsular Malaysia Using the Analytic Network Process (ANP) Method

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ABSTRACT

The rise of radicalism poses a significant threat to societal peace and national stability. This has led to the need for effective predictive measures as an early prevention step. Using the Analytic Network Process (ANP) method, this study predicts the occurrence of radicalism in Peninsular Malaysia. The study identifies 15 indicators across four clusters—social, political, economic, and modernisation—that influence susceptibility to radicalism. By applying the ANP method, the study determines the weight of each indicator and develops a radicalism susceptibility map. Geospatial analysis is conducted using GIS tools to visualise the research findings. The accuracy of the generated predictive map is validated through the AUC-ROC method. The susceptibility model achieved an accuracy rate of 65% in AUC-ROC validation. This research contributes to a deeper understanding of the factors driving radicalism in Malaysia and provides valuable insights to stakeholders for controlling and preventing radicalism threats in potential areas, thereby enhancing national security.

Keywords: Radicalism prediction; geospatial; Analytic Network Process (ANP); radicalism susceptibility; Peninsular Malaysia

INTRODUCTION

The rise of radicalism has significantly altered the political, social, and economic landscape, posing a threat to national peace and harmony (Office of the United Nations High Commissioner for Human Rights 2008). Radicalisation primarily manifests in two forms: first, violent radicalisation, which focuses on the active pursuit or acceptance of violence to achieve specific objectives; second, a broader type of radicalisation that seeks extensive societal changes, potentially endangering democracy and sometimes involving violence (Veldhuis & Staun 2009) . As noted by (Pauwels et al. 2014), radicalism is a precursor to terrorism, though incidents of radicalism are less frequent. While radicalism typically has a minimal impact on individuals, the environment, and infrastructure compared to the widespread destruction caused by terrorism, its effects on a country's socioeconomic condition are less easily quantifiable.

Terrorism and radicalism are longstanding issues worldwide that have garnered significant research interest aimed at understanding their causes, impacts, and prevention strategies. While terrorism has been extensively studied due to its immediate security implications, radicalism has received comparatively less attention, often regarded as a social or ideological concern. Over time, research on radicalism has gradually increased, particularly in efforts to map the distribution of radical incidents and identify hotspots. However, there remains a lack of studies focused on predicting future incidents based on various contributing factors. Developing predictive models is essential for effective prevention and intervention strategies in addressing radicalism.

Predictive technologies play a vital role in the early detection and effective management of potential violent incidents (Brown, Dalton & Heidi 2004). Recent advancements, particularly in relational database methodologies, have enabled new efforts to forecast terrorist group activities. However, these initiatives often overlook critical temporal and spatial relationships (Cothren et al. 2008). Since radicalism incidents are influenced by both geographical and non-geographical factors, creating a predictive model that does not incorporate spatial considerations is insufficient. To effectively address radicalism, it is crucial to focus on the specific locations that are more prone to such incidents (Hirscgfield & Bowers 2017).

Radicalism in Malaysia and other nations may share common goals related to ethnicity and religion, yet notable differences exist between these contexts. In Europe, radicalism encompasses political, social, or religious ideologies that advocate for significant changes to existing governance systems, economies, or religious practices. The rise of radicalism in Europe has been driven by various factors, including economic challenges, increasing cultural and ethnic diversity, and the emergence of right-wing populist movements. Concerns over Islamic radicalism have intensified, especially following terrorist attacks. Research by (Okeniyi et al. 2018) has highlighted how environmental issues, such as temperature fluctuations and drought, can contribute to terrorism incidents in Kenya. Compared to radicalism incidents that happened in Malaysia, such as; 13 May, Kampung Rawa and Kampung Medan riot, Al-Mauanah group attack, a bomb attack at Movida bar, and the latest incidence is Seri Maha Marimam temple incidents show that Malaysia's radicalism factor is mostly related to achieve the ethnic and religion goal showing that Malaysia rarely involves environmental issues in radicalism incidents.

There are still very few studies that specifically concentrate on forecasting radicalism episodes, despite the fact that there is an increasing global worry about radicalism (Jamal et al. 2023). Some methods, such as the utilisation of temporal and spatial distribution patterns, have been used to predict radicalism (Chen and Mu, 2021;Gao et al. 2013; Jha, 2009; Brown et al. 2004). Additionally, several studies have used machine learning techniques including random forest (RF) (Hao *et al.* 2019; Basu et al. 2017), k-Nearest Neighbours (KNN) (Kalaiarasi et al. 2019), and other machine learning techniques (Siebeneck et al. 2009; Maniraj et al. 2019). Even with all of the methods employed, the geographic approach to incidence prediction is still not fully integrated (Jamal et al. 2023). There has been little research done in Malaysia to forecast the prevalence of radicalism, and no research has been done there to map radicalism susceptibilities.

Few studies are focusing on predicting incidents related to violent acts, terrorism, extremism and radicalism. If there are, only a few of them are focusing on applying geospatial in predicting such incidents. From the previous study, some implementation can be done to fill the gaps and issues related to the geospatial.

Radicalism has transformed the environment and created a serious challenge for many countries in recent years. Apart from that, radicalism have been increasingly subjected to scientific study. As stated by Political (Soomro, 2011), a political response is needed to prevent radicalism, and the use of the latest technology tools and techniques are required to prevent a terrorist attack. In line with Soomro, nowadays, many technologies are involved in radicalism, including applying Geographic Information System (GIS). Recently, geospatial had been used to analyse Spatio-temporal patterns of terrorist and radicalism incidents. Geospatial, without a doubt, plays a crucial role in combating terrorism (Soomro, 2011).The geospatial approach provided geographical connections that would otherwise be neglected or ignored in traditional terrorism and counter-terrorism research (Henkin et al. 2020).

Apart from that this study is focusing on predicting radicalism incidence in Peninsular Malaysia by taking part the factor of the occurrence. In making sure the predicting result produced based on the real situation, geospatial approach together with Analytic Network Process (ANP) method was used. ANP is used to determine the weightage and the ranking of each indicator and sub-indicator while geospatial was mainly used to run the overlay proses and to visualise the result.

THEORETICAL BACKGROUND

ANALYTIC NETWORK PROCESS (ANP)

ANP computes complex relationships between decision elements through replacement of a hierarchical structure with a network structure. ANP has all the positive features of AHP, including simplicity, flexibility, simultaneous use of quantitative and qualitative criteria and ability to review consistency in judgments. ANP considers each issue as a network of criteria, sub-criteria and alternatives. All elements in a network can communicate with each other in any way. In other words, in a network, feedback and interconnection are possible between clusters. ANP technique can be summarised in four steps as follows step (Saaty & Hall 1999).

The ANP model compares in pairs with relative weight estimation and formation of supermatrix, and adopts supermatrix weight of which is two factors in 15 indicator to choose the best way (Saaty 1987). Therefore, this rule that is the ANP comparing two relative weights is followed to build the most adaptive model, as shown in Figure 1.

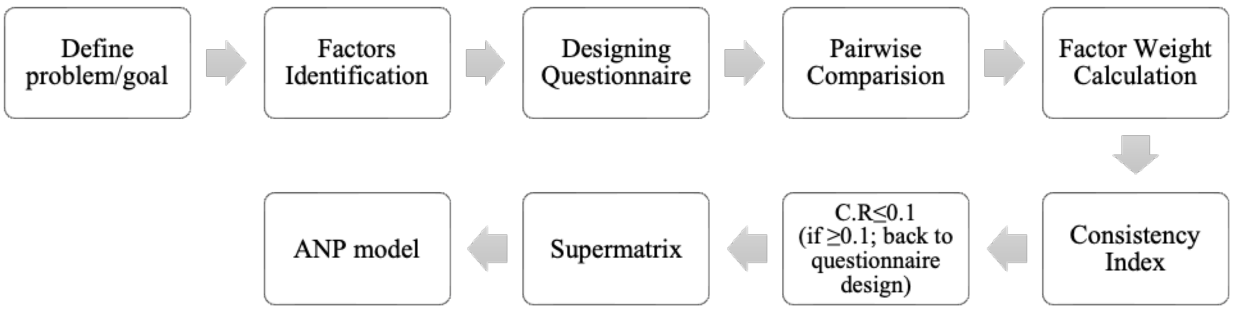


FIGURE 1. Flow method of ANP model

To conclude the flow chart in figure 1 ANP model process is divided into four steps as follows:

1. Pairwise comparison and relative weight
2. Formation of initial supermatrix
3. Formation of weighted supermatrix
4. Calculation of global priority vectors and weights.

STEP I: PAIRWISE COMPARISON AND RELATIVE WEIGHT

A problem must be transformed into a logical system, such as a network, openly. This network structure can be obtained through brainstorming. At this point, the problem is converted into a network structure, where all elements can communicate with each other. Like pairwise comparison performed in AHP, decision elements in each cluster are compared pairwise. Clusters themselves are also compared based on their role and effect on achieving goals as well as interdependence between criteria of each cluster.

Saaty (1987) proposed a scale from 1 to 9 for these comparisons as stated in Table 1. Figure 2 presents a sample questionnaire designed for cluster comparison in this study, which is then evaluated using a calculation involving relative weights and a consistency index. Experts from the related field will complete the questionnaire to assign weights to various indicators. The formula for pairwise comparison by (Saaty, 1987) is provided in Equation 1,2,and 3.

$$A = \begin{bmatrix} 1 & a_{12} & a_{1n} \\ 1/a_{12} & 1 & a_{2n} \\ 1/a_{1n} & 1/a_{2n} & 1 \end{bmatrix} = \begin{bmatrix} w_1/w_2 & w_1/w_2 & w_1/w_n \\ w_2/w_1 & w_2/w_2 & w_2/w_n \\ w_n/w_1 & w_n/w_2 & w_n/w_n \end{bmatrix} \quad (1)$$

W_i: weight of the main element i;i = 1, 2, 3, . . n; a_{ij}: ratio between two main elements i, j = 1,2,3, n

$$a_{ij} = 1/a_{ij} \text{ and } a_{ik} = a_{ij} * a_{jk} \quad (2)$$

$$W = [w_k], \text{ where } w_k = \sum_{j=1}^{n} a'_{ij}/n \quad (3)$$

Although a pairwise comparison matrix is a positively reciprocal matrix, a policymaker may find it challenging to achieve a consistent evaluation of the main elements. To address this, it is essential to assess consistency in order to calculate the consistency index (CI). This step helps filter the information and ensures that the results accurately represent real conditions. The value of a_{ij} in the positive reciprocal matrix can vary significantly with even minor changes in the λ_{max} value. Therefore, it is possible to establish a difference between two levels of λ_{max} intensity and the corresponding consistency level of the evaluation criteria. The defining formula is presented in Equation 4.

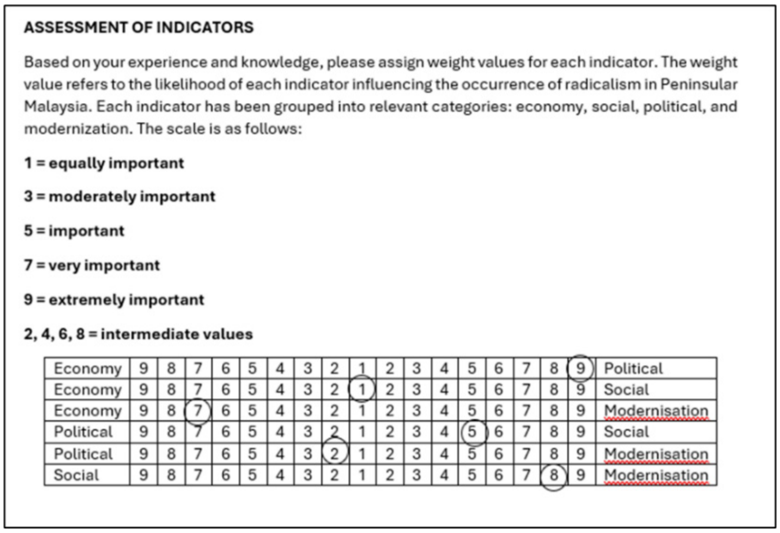
$$C.I = \frac{\lambda_{max} - n}{n-1} \quad (4)$$

number of assessing elements

The system's policymaker considers the consistency index (C.I.) to be acceptable at a value of 0, while a C.I. greater than 0.1 indicates inconsistency. According to (Saaty, 1987), a deviation is deemed acceptable if the C.I. is less than or equal to 0.1

TABLE 1. Scale of Analytic Hierarchy Process (ANP) (Saaty, 1987)

Degree of Preference	Definition	Explanation
1	Equal importance	Both criteria are equally important, or both the factors have same effect on the occurrence of radicalism
3	Moderately Important	One factor is more effective as compared to the other factor
5	Highly Important	One factor affects highly as compared to the other factor
7	Very Highly Important	A factor is highly dominated over other
9	Extremely Important	A factor has the highest possibility of affecting the occurrence of radicalism over another factor
2, 4, 6, 8	Intermediate values	If a compromise between two factors is required, intermediate values can be used



ASSESSMENT OF INDICATORS

Based on your experience and knowledge, please assign weight values for each indicator. The weight value refers to the likelihood of each indicator influencing the occurrence of radicalism in Peninsular Malaysia. Each indicator has been grouped into relevant categories: economy, social, political, and modernization. The scale is as follows:

1 = equally important

3 = moderately important

5 = important

7 = very important

9 = extremely important

2, 4, 6, 8 = intermediate values

Economy	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Political
Economy	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Social
Economy	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Modernisation
Political	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Social
Political	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Modernisation
Social	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Modernisation

FIGURE 2. Questionnaire for cluster comparison

STEP II: FORMATION OF INITIAL SUPERMATRIX

Table 2 presents the weights of each indicator and the corresponding eigenvector, derived from the data in Figure 2. The consistency index ensures that the calculation reflects actual conditions. These weights are used to create the first supermatrix. Table 3 illustrates the first supermatrix obtained by calculating the weight values and organising them as outlined in Step 1.

STEP III: FORMATION OF WEIGHT SUPERMATRIX

The Step II initial supermatrix is adjusted to ensure that the sum of each column equals one. Table 4 shows the weight supermatrix.

STEP IV: LIMITING SUPERMATRIX

The final supermatrix is achieved by repeatedly multiplying the initial supermatrix by a stable value of disaster factors (2(n – 1) multiplications). This process results in the terminal supermatrix. Table 5 illustrates how the weights of the supermatrix are derived through element-by-element multiplication of the initial supermatrix and the limiting supermatrix, which contains global priority weights. The supermatrix weights are elevated to a power weight until convergence is reached. In this study limiting supermatrix is generated using Super Decision software.

MATERIAL AND METHOD

In the present study, 15 indicators from 4 class of cluster consist of social, politic, economic and modernisation was used. Indicator from involved cluster consist of household income, poverty, financial issues, inequality, mental issues, age, numbers of radicalism, crime, abused cases, religion obsession, political issue, influence of politicians, internet speed and rate of internet subscription are used to achieve a radicalism susceptibility map in Peninsular Malaysia. All sub-indicators involved were present in table 6. After collecting and reviewing the factors related to the study area, an attempt was made to provide a general framework for preparing a radicalism susceptibility map. In this study, a radicalism susceptibility map was prepared using ANP methods to support geospatial approach (overlay method).

STUDY AREA

This research focuses on Peninsular Malaysia, which covers a geographical area of 131,598 km^2, located between latitudes 20°N and 6°40′N, and longitudes 99°35′E and 104°20′E. Figure 3 show the map of Peninsular Malaysia which consist with 12 states. Each states has their districts boundaries within the state area. As of the 2022 census, Malaysia has a population of 32.4 million, with ethnic and religious diversity, including Islam (63.5%), Buddhism (18.7%), Christianity (9.1%), Hinduism (6.1%), and others. Malaysia is relatively peaceful, ranked 10th in the Global Peace Index (GPI) with a score of 1.427 in 2024 (Institute for Economics & Peace, 2024), and it has experienced low levels of terrorism and radicalism.

Based on historical record, incidents of radicalism persist, especially in Selangor and Johor, often involving religious and ethnic issues. Past radicalism incidents highlighted the unique pattern of radicalism incidents in Peninsular Malaysia, with occurrences at worship places, government buildings, and public areas. This research focuses on district as the unit of analysis to better predict radicalism locations and provide valuable insights for authorities and stakeholders to counter radicalism.

FIGURE 3. Study area map (Peninsular Malaysia)

METHOD DESCRIPTION

In this paper, the general process presented in Figure 4 is used to prepare radicalism susceptibility maps of the study area. In the first step, different indicators were determined to address the studied subject including household income, poverty, financial issues, inequality, mental issues, age, radicalism, crime, abused cases, religion obsession, political issues, influence of politicians, internet speed and rate of internet subscription. After identifying these indicators, they were categorised as major indicator and sub-indicator. Step 3 is focusing on calculating the weight of indicator using the ANP method while step 4-7 involved the geospatial approach in mapping the prediction map.

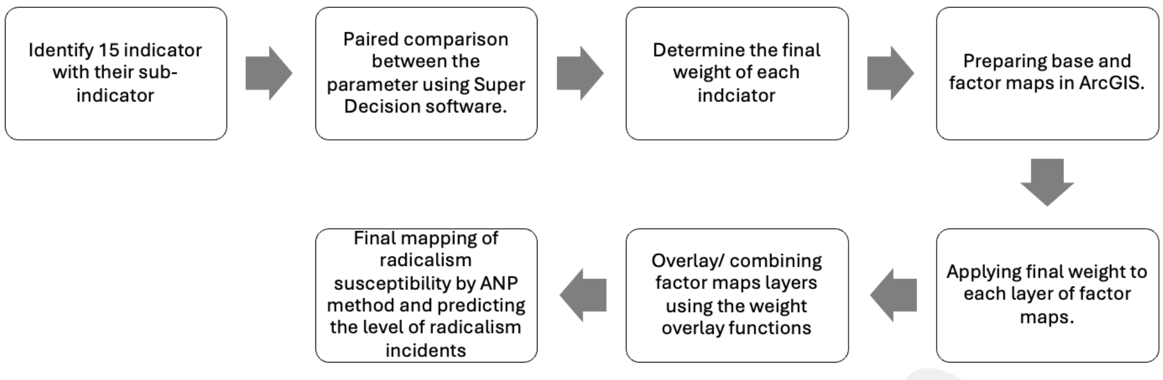


FIGURE 4: Flow chart in Mapping Radicalism Prediction.

DATA PREPARATION

Base map of Peninsular Malaysia district map was managed in shape file (.shp) format to generate factor class map for each indicator. Base map in .shp then was convert into raster format; each cell of the grid having a dimension of 220×220 m. Priority weights obtained from the ANP model would be integrated with the cell information to evaluate the stability assessment of individual cell in generating the susceptibility value.

RADICALISM INDICATOR IDENTIFICATION

Determining the factors affecting incidents is one of the essential steps in mapping the susceptibility of an incident. In this study, the 15 factors influencing radicalism are household income, poverty, financial issues, inequality, mental issues, age, numbers of radicalism, crime, abused cases, religion obsession, political issues, influence of politicians, internet speed and rate of internet subscription. All these factors had been determined after had undergoes several processes including interviewed with questionnaire by expert. 14 government officials and academic experts with over five years of expertise in the subject of radicalism participated in this study.

Returned questionnaire forms were analysed using Relative Important Index (RII) method to determine the suitability of each indicator based on expert agreement. The formula adopted for RII is show Equation 5.

$$C.I = \frac{\lambda_{max} - n}{n-1} \tag{5}$$

Where ‘w’ is the score as assigned by each respondent on a scale 1 to 9. A is the highest score (9), and N is the total number of the sample. Then in determining acceptance and rejected of the indicator list of step below was calculated. Indicator with result “Least Important” were rejected.

Calculate the mean importance index (M) for each MC item.

1. For each resource, identify the one standard deviation (A) of MC items higher than M. The MC item with an importance index value higher than A is categorised as Very Important.
2. The MC item with an importance index value between M and A is categorised as “Important”.
3. Identify the one standard deviation (B) of the MC item lower than M. The MC item with an importance index value between M and B is categorised as Somewhat Important.
4. The MC item with an important index value lower than B is categorised as “Least Important”

Out of 20 indicators had been listed 15 indicator had scored very important, important and somewhat important. All those 15 indicators are household income, poverty, financial issues, inequality, mental issues, age, numbers of radicalism, crime, abused cases, religion obsession, political issue, influence of politicians, internet speed and rate of internet subscription. All factor maps were created using data in 2022, which main source of the data was government agency. By collecting data of 15 factors affecting radicalism incidents, a database was created to store all the factor data. Using the ArcMAP from the ArcGIS software, all data had been stored in geodatabase, and each indicator had been geospatialised into factor maps. Each indicator was divided into several classes. The factor class map classification of each indicator was done by the Natural break method to perform ANP analysis and also for better display. Figure 5 until Figure 18 visualised the class factor for each factor included in this study.

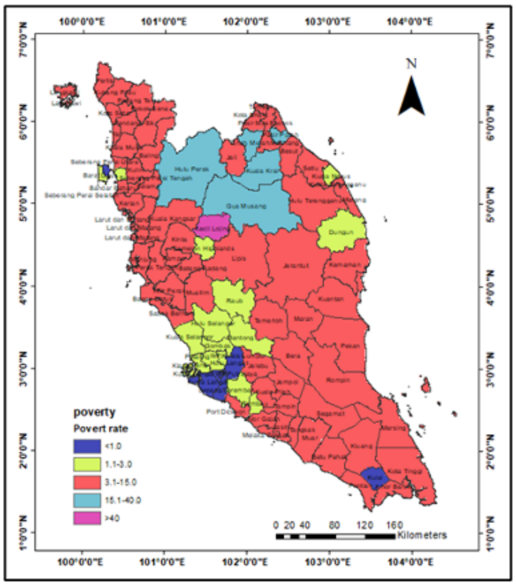


FIGURE 5. Distribution map of poverty rate

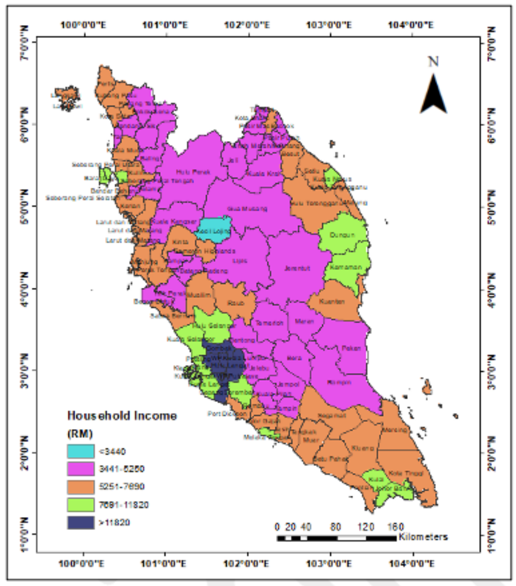


FIGURE 6. Distribution map of household income

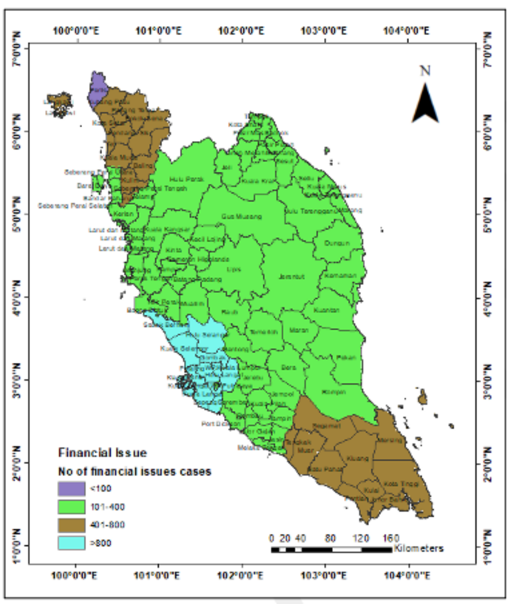


FIGURE 7. Distribution map of financial issues cases

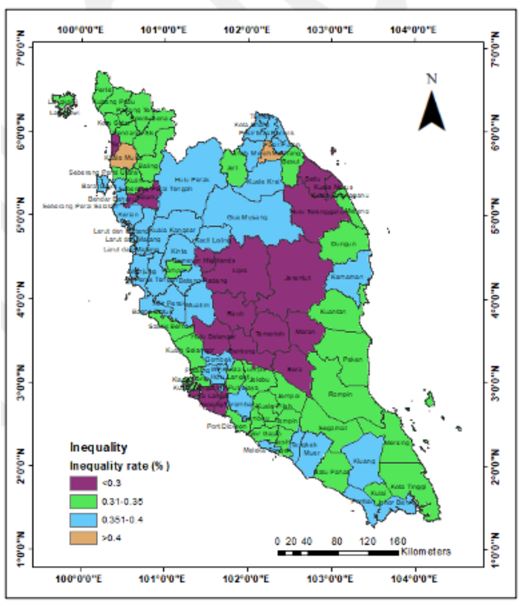


FIGURE 8. Distribution map of inequality rate

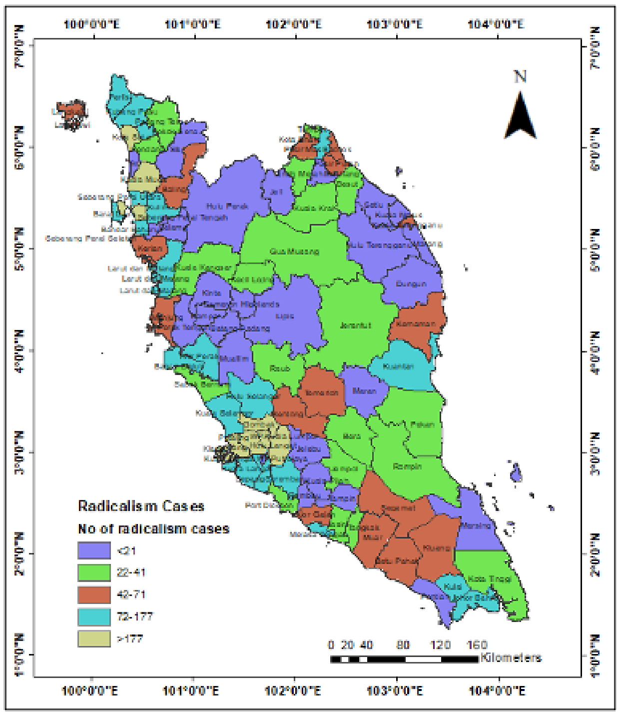


FIGURE 9. Distribution map of radicalism cases

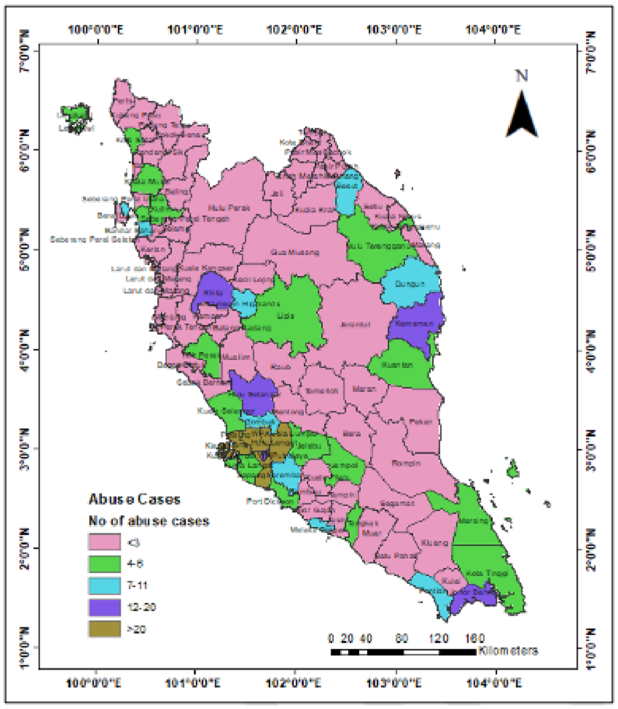


FIGURE 10. Distribution map of abuse cases

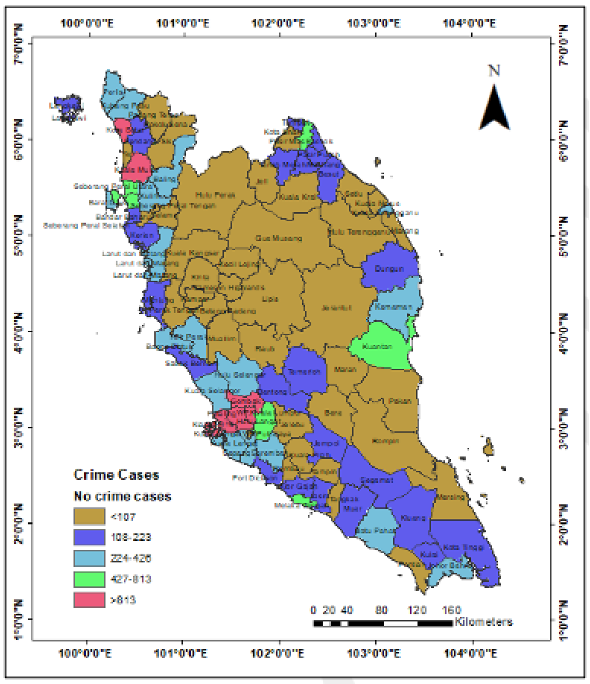


FIGURE 11. Distribution map of crime cases

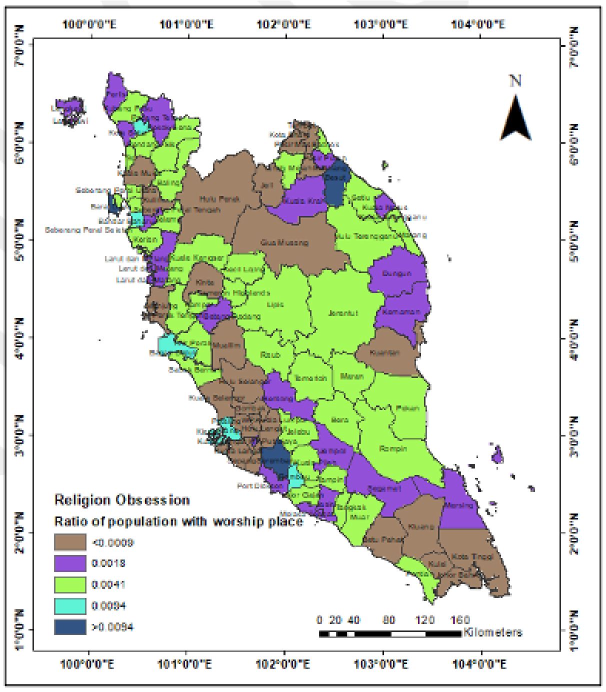


FIGURE 12. Distribution map of religion obsession

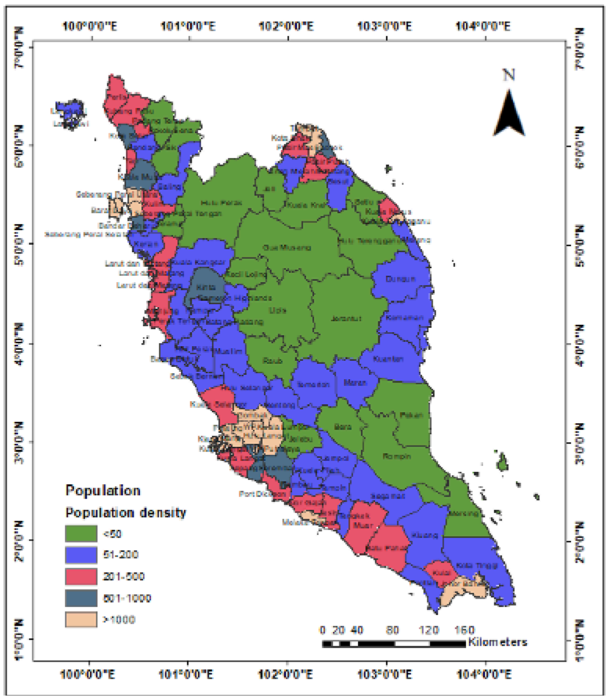


FIGURE 13. Distribution map of population density rate

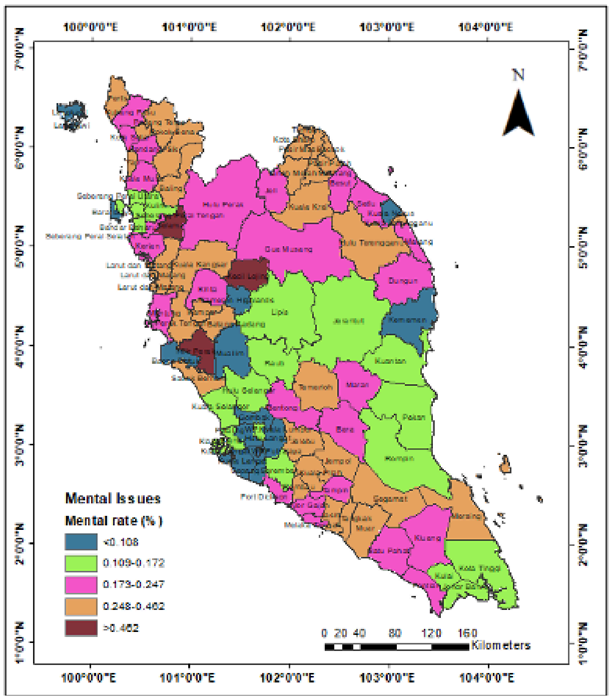


FIGURE 14. Distribution map of population density rate

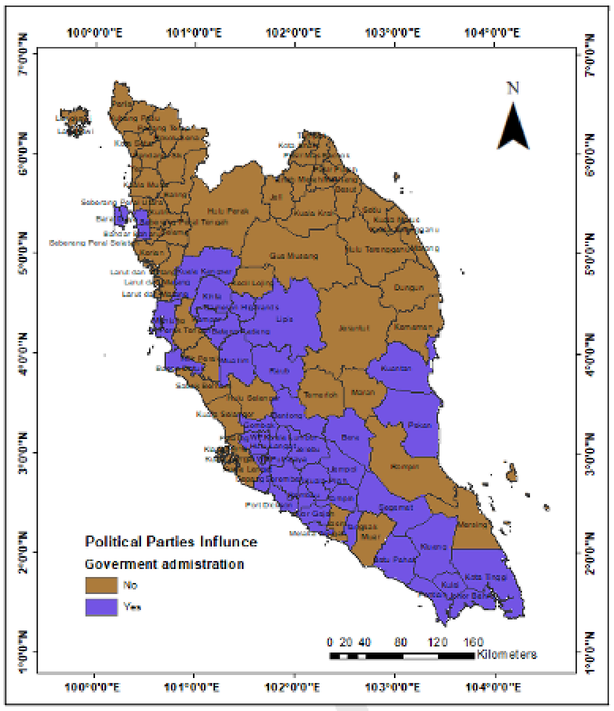


FIGURE 15. Distribution map of political party's influence

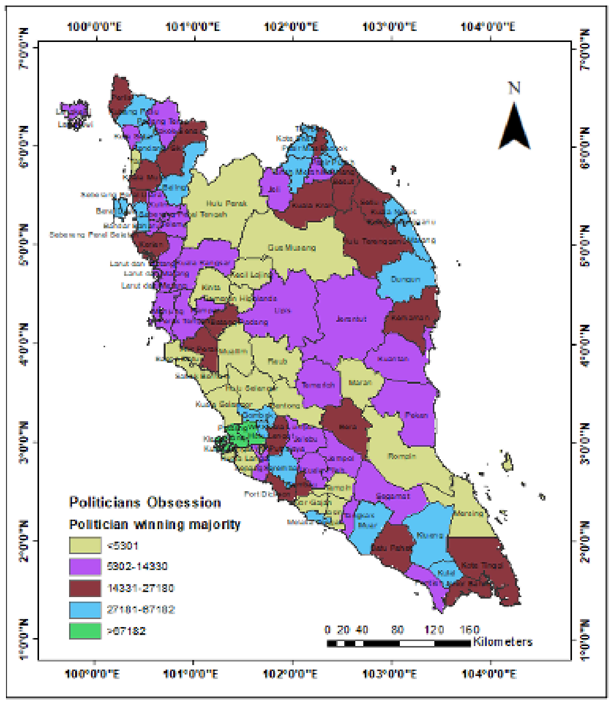


FIGURE 16. Distribution map of politicians winning majority

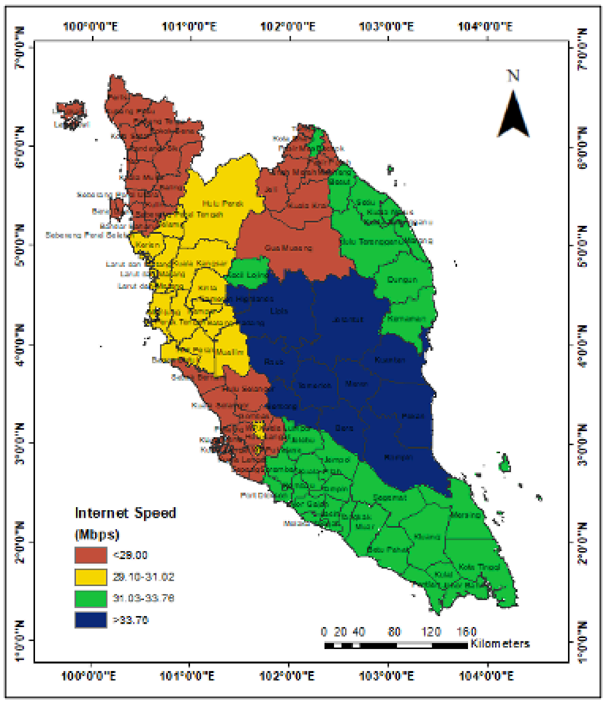


FIGURE 17. Distribution map of internet speed

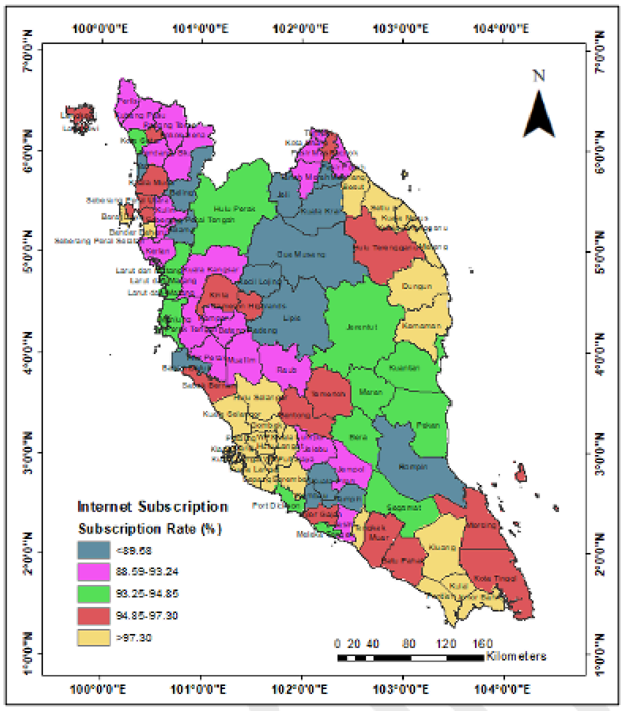


FIGURE 18. Distribution map of internet subscription rate

POVERTY RATE

Poverty levels are categorised into five groups based on the percentage of poor people in an area. Areas with a low poverty rate are very low, while those with a high rate are very high. High poverty rates indicate significant economic challenges, dissatisfaction, and marginalisation. Higher poverty rates increase vulnerability to radicalism, especially when combined with other factors.

HOUSEHOLD INCOME

Household income used in radicalism prediction was also support by a research by (Nawaz, 2024) that had a identified statistically significant negative relationship between family income and radicalisation. Individuals from lower-income households are more susceptible to radical ideologies. In this study household income was categorised into five levels based on the range of monthly income in Ringgit Malaysia (RM). Households earning less than RM3,440 were placed in the very high category, while those earning between RM3,441 and RM5,250 were classified as high. Next, households with income between RM5,251 and RM7,690 were classified as medium. For those earning between RM7,691 and RM11,820, they were classified as low. Finally, households with income above RM11,820 were categorised as very low.

FINANCIAL ISSUES

This indicator is closely linked to poverty and household income, emphasising financial issues , (Che-Yahya et al. 2023). Previous studies by (Luo & Qi, 2021 & Youngblood, 2020)also support the correlation between these indicators and radicalism. Specifically, insolvency cases are categorised into four levels based on frequency: areas with fewer than 100 cases are associated with very low susceptibility to radicalism, while those with 101-400 cases show low susceptibility; 401-800 cases indicate high susceptibility; and areas exceeding 800 cases face very high susceptibility. A rise in insolvency cases typically signifies economic distress, potentially enhancing vulnerability to radical influences.

INCOME INEQUALITY

This is support by a research by (IMAN RESEARCH, 2019)which highlights that economic disenfranchisement, such as unemployment and income inequality, can lead to feelings of alienation. The level of income inequality has been classified into four categories based on the Gini coefficient value, which measures the income gap between the rich and the poor. Areas with a Gini value of less than 0.300 are categorised as very low and show very low susceptibility to radicalism, as a more balanced income distribution tends to contribute to social harmony. Next, areas with a value between 0.310 and 0.350 are classified as low susceptibility, which still indicates a fair economic situation despite a slight gap. However, when the Gini value increases to between 0.351 and 0.400, the area is in the high susceptibility category, indicating a more significant income inequality and can lead to dissatisfaction among low-income communities. Finally, areas with a value above 0.400 are categorised as very high susceptibility.

MENTAL ILLNESS

Mental health case rates have been classified into four categories based on the proportion of cases in an area. Areas with rates between 0.109 and 0.172 are categorised as very low and show very low susceptibility to radicalism, as better mental wellbeing is generally associated with emotional and social stability. Areas with rates between 0.173 and 0.247 are placed in the low susceptibility category, indicating that some mental health issues are present but are still under control. However, when rates rise to between 0.248 and 0.462, the area is classified as high susceptibility, indicating an increase in mental disorders that can affect an individual's psychological resilience to social stress. Finally, rates above 0.462 indicate that the area is in the very high susceptibility category, which may reflect a large psychosocial burden in the community, as well as increasing the potential vulnerability to the influence of radicalism. Overall, the increase in mental health case rates could be an indicator of greater social stress, which in turn contributes to the risk of radicalisation among the population.

AGE

The incidences of radicalism were influenced by age, particularly youth as a targeted demographic (Rhazzali & Schiavinato, 2023). Furthermore, teenagers may be more vulnerable to radicalism as a result of their need for identity and a sense of belonging. (Philipp et al. 2022).This is consistent with the subclass off age, which indicates that the age group most likely to initiate radical occurrences is 19–39.

ABUSE CASE

Abuse cases whether physical, emotional or neglect can contribute to radicalism where experiences of abuse, can influence pathways into and out of radicalism. (Smart & Brown, 2022).Abuse cases have been classified into five levels based on the number of cases recorded in an area. Areas that recorded less than 3 cases are categorised as very low and show very low susceptibility to radicalism, due to a safer and more stable social environment. Next, areas with 4 to 6 cases are in the low susceptibility category, which indicates the existence of abuse incidents but are still under control. For areas that record 7 to 11 cases, it is classified as medium susceptibility, which may reflect social pressure or a failure in the community protection system. Meanwhile, areas with 12 to 20 cases are placed in the high susceptibility category, indicating a worrying level of abuse and the potential to disrupt emotional stability and social relationships. Finally, areas with more than 20 cases are categorised as very high susceptibility, which reflects a high-risk social environment and can contribute to individual psychological instability, distrust of the social system, as well as increasing the potential for exposure to the influence of radicalism. Overall, the increase in abuse cases not only signals a failure of social protection but can also be a catalyst for deep dissatisfaction and the acceptance of radical ideas as a form of response or escape from the suffering experienced.

PAST RADICAL CASE

Past radical cases were classified into five categories based on the number of incidents: very low (fewer than 21 cases), low (22-41 cases), medium (42-71 cases), high (72-177 cases), and very high (more than 177 cases). Very low areas show minimal radical involvement and high stability, while high and very high areas indicate significant historical radical activity, suggesting the potential for recurrence. The classification reflects the likelihood of existing networks contributing to radicalism, with more cases correlating to greater susceptibility.

PAST CRIME CASE

Crime cases have been classified into five categories based on the number of cases recorded in an area. Areas that recorded less than 107 cases are categorised as very low and show very low susceptibility to radicalism, as high levels of security are usually closely linked to social stability. Next, areas with 108 to 223 cases are in the low category, which still shows a relatively safe social situation. For areas with 224 to 426 cases, it is classified as medium, reflecting an increase in criminal activity that may affect the sense of security in the community. Areas with a number of cases between 427 to 813 belong to the high category, indicating a worrying level of crime that can disrupt public well-being and confidence in enforcement institutions. Finally, areas with more than 813 cases are classified as very high susceptibility, indicating an unstable and high-risk social environment, thus increasing the potential for the population to be exposed to the influence of radicalism, especially in situations where justice is perceived to have failed. Overall, increased crime rates can create an atmosphere of distrust, fear and social pressure, which are among the contributing factors to vulnerability to radicalisation.

POPULATION DENSITY

Next was population density. population density can influence radicalism incidents, often through mechanisms like social dynamics. High population brings to social diversity. Densely populated areas may provide environments encouraging radicalism due to increased anonymity and exposure to diverse ideologies. privacy, and exposure to diverse ideas (Gruenewald et al. 2021). Population density has been classified into five categories based on the number of people per square kilometre in an area. Areas with less than 50 people per km² are categorised as very low and show very low susceptibility to radicalisation, as small communities are usually closer together and easier to monitor socially. Areas with a density of between 51 and 200 people per km² are in the low susceptibility category, which still maintains a controlled and stable community atmosphere. Areas with 201 to 500 people per km² are categorised as medium susceptibility, where moderate population growth may bring challenges in terms of public facilities, social pressures and employment opportunities. Meanwhile, areas with densities between 501 and 1000 people per km² are classified as high (high susceptibility), indicating a more densely populated area with the potential to face problems such as congestion, resource competition, and social tension. Finally, areas with more than 1000 people per km² are classified as very high susceptibility, indicating a greater risk of social stress, inequality, and alienation in densely populated communities, thus potentially contributing to increased susceptibility to the influence of radicalism.

RELIGIOUS OBSESSION

The last indicator for social cluster was religion obsession. Religious obsession can lead to radicalism, particularly when such obsession is linked with psychological vulnerabilities, social separation, and ideological manipulation. Individuals with these symptoms may become excessively stuck on religious ideologies, leading to rigid thinking and susceptibility to extremist action. (Troian & Bélanger, 2024). Malaysia's diverse religious landscape and the presence of various religious ideologies force a nuanced approach to countering radicalism, focusing on promoting critical thinking, mixed dialogue, and psychological resistance. For this indicator, rate of religion obsession was measure based on rate of Islamic school to nation school. This is because its is difficult to measure individual religious level. High rate indicted to the high ranking of religious obsession.

POLITICAL PARTIES INFLUENCE

Political party influence refers to whether a region is under the administration of a ruling party or not, which reflects the level of power in administrative decision-making. Areas under the ruling party (Yes) are considered to have greater access to resources and development policies and are therefore categorised as not susceptible to radicalism. This is because these areas typically benefit from administrative stability and continuous aid channels, which can reduce dissatisfaction among the population. Conversely, areas not under the administration of a ruling party (No) are likely to face constraints in service delivery and policy attention and are therefore categorised as susceptible to radicalism. In this context, the absence of direct administrative power can lead to a sense of marginalisation or dissatisfaction with the government, thus increasing the risk of susceptibility to radicalism, especially among groups that feel neglected.

POLITICIAN INFLUENCE

The influence of politicians is measured by the majority margin of votes obtained during a general election, which reflects the level of support or attachment of the public to a particular political individual. Areas with a majority margin of less than 5,301 votes are categorised as very high susceptibility to radicalism, as it reflects weak support and may reflect political instability or division of views among voters. For margins between 5,302 and 14,330 votes, these areas are in the high susceptibility to radicalism, indicating that there is still political uncertainty despite some dominance. Next, margins of 14,331 to 27,180 votes are classified as Medium, reflecting a moderate level of political stability and medium susceptibility to radicalism. When the margin increases to between 27,181 and 67,182 votes, the area falls into the category of low susceptibility to radicalism as a result of strong political support and the strong influence of the leader on the community. Finally, areas with margins exceeding 67,182 votes are categorised as very low susceptibility to radicalism, as the level of public trust and attachment to political leaders is very strong, thus contributing to social and political stability.

INTERNET SPEED

Internet speed plays an important role in determining the level of access to information and the connectedness of society to the outside world. Based on the classification, areas with internet speeds of less than 25 Mbps are categorised as very low, indicating a very low level of susceptibility to radicalism. This indicates that these areas may be less exposed to potentially extreme external influences. Next, speeds between 26 and 30 Mbps are considered low, indicating low susceptibility to radicalism. The range of 31 to 35 Mbps is categorised as high, indicating high susceptibility to radicalism, possibly due to exposure to various uncensored online sources. Finally, areas with speeds above 35 Mbps are classified as very high, indicating a very high susceptibility to radicalism, as the widespread level of digital access and influence can open up space for the spread of radical ideas

INTERNET SUBSCRIPTION RATE

Internet subscription rates represent the percentage of the population with active internet access, which may influence exposure to online information and digital content. In this study, lower subscription rates are associated with lower susceptibility to radicalism due to limited exposure to online radical materials, while higher subscription rates indicate greater susceptibility because of increased digital connectivity and access to radical digital propaganda.

ANP MODEL FOR RADICALISM SUSCEPTIBILITY

The ANP model is represented by a network structure indicating all dependences among clusters and determining the direction of influences. Figure 19 illustrates ANP model for radicalism susceptibility for this study. As shown in the figure 19, connections were set among elements within a cluster (inner dependence) and between clusters (outer dependence). In a cumulative view, a cluster is connected to another when at least one of its elements is connected to at least one element of the other cluster.

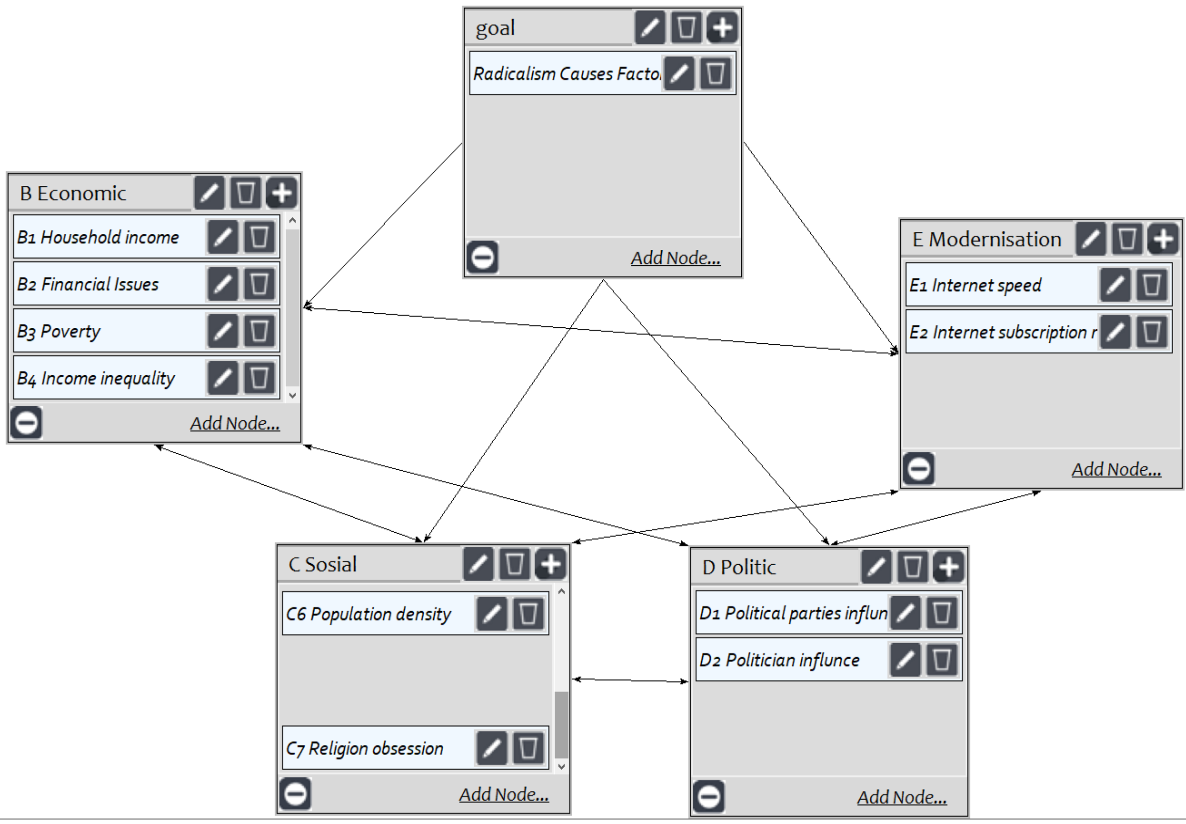


FIGURE 19. Cluster network of ANP model in predicting radicalism incidents

For the initial supermatrix calculation, pairwise comparisons were done between all indicator influenced by other indicator within the same cluster (nodal comparison). Relative weight vectors were calculated using Eq. (1)-(4). The matrix of relative weight vectors is called the initial supermatrix, which was multiplied by cluster weights, element by element, to arrive at the weighted supermatrix. Figure 2 shows a sample of questionnaire used for cluster comparison, and a sample calculation for relative weight and consistency index. A similar procedure was followed for nodal comparisons.

In this study to prepare the final radicalism susceptibility map, the final weights of the ANP method must first be calculated using the Super Decision software. Then, unweighted, weighted and the limit matrix is formed, and the weight of each cluster is determined. Table (3) until Table (5) present the result of the unweighted supermatrix, weighted supermatrix and the limit supermatrix. Table 6 shows the relative weights of the cluster and indicator using the ANP method in the Super Decision software environment. Finally, the factor class map of all indicators is imported in the ArcMap software, and the layers are combined and the final radicalism susceptibility map in the study area is represented in Figure 21 Then the accuracy of the generated result is validated using the AUC ROC method. All result was represented in next sub section.

RESULT AND ANALYSIS

This subsection will present result from all of the ANP process and also the final product of this study, Prediction map of Radicalism in Peninsular Malaysia

WEIGHT CALCULATION RESULT

a. Cluster weight

TABLE 2. Vector of each factor

	B Economic	C Social	D Politic	E Modernisation	Eigenvector
B Economic	1	1/4	3	1/2	0.152
C Social	4	1	4	3	0.523
D Politic	1/3	1/4	1	1/4	0.077
E Modernisation	2	1/3	4	1	0.248
λ_max = 4.17503		C.R = 0.064153			

b. Unweighted supermatrix

TABLE 3. Unweighted pairwise comparison

		B Economic				C Sosial							D Politic		E Modernisation		
		B1	B2	B3	B4	C1	C2	C3	C4	C5	C6	C7	D1	D2	E1	E2	Goal
B Economic	B1	0.000	0.000	0.000	0.000	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330
	B2	0.000	0.000	0.000	0.000	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
	B3	0.000	0.000	0.000	0.000	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330	0.330
	B4	0.000	0.000	0.000	0.000	0.140	0.140	0.140	0.140	0.140	0.140	0.140	0.140	0.140	0.140	0.140	0.140
C Social	C1	0.110	0.110	0.163	0.110	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.183	0.110	0.110	0.117	0.110
	C2	0.079	0.079	0.110	0.079	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.127	0.079	0.079	0.077	0.079
	C3	0.237	0.237	0.173	0.237	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.170	0.237	0.237	0.236	0.237
	C4	0.063	0.063	0.153	0.063	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.091	0.063	0.063	0.060	0.063
	C5	0.161	0.161	0.143	0.161	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.122	0.161	0.161	0.161	0.161
	C6	0.043	0.043	0.066	0.043	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.087	0.043	0.043	0.043	0.043
	C7	0.306	0.306	0.193	0.306	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	0.306	0.306	0.305	0.306
D Politic	D1	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.000	0.000	0.667	0.667	0.667
	D2	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.000	0.000	0.333	0.333	0.333
E Modernisation	E1	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.667	0.000	0.000	0.667
	E2	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.000	0.000	0.333
Goal	goal	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

c. Weighted supermatrix

TABLE 4. Weighted pairwise comparison

		B Economic				C Social							D Politic		E Modernisation		
		B1	B2	B3	B4	C1	C2	C3	C4	C5	C6	C7	D1	D2	E1	E2	goal
B Economic	B1	0.000000	0.000000	0.000000	0.000000	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998
	B2	0.000000	0.000000	0.000000	0.000000	0.199581	0.199581	0.199581	0.199581	0.199581	0.199581	0.199581	0.199581	0.199581	0.199581	0.199581	0.199581
	B3	0.000000	0.000000	0.000000	0.000000	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998	0.329998
	B4	0.000000	0.000000	0.000000	0.000000	0.140424	0.140424	0.140424	0.140424	0.140424	0.140424	0.140424	0.140424	0.140424	0.140424	0.140424	0.140424
C Social	C1	0.109974	0.109974	0.162574	0.109974	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.183123	0.109974	0.109974	0.116711	0.109974
	C2	0.078944	0.078944	0.109650	0.078944	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.127051	0.078944	0.078944	0.077391	0.078944
	C3	0.236622	0.236622	0.173044	0.236622	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.170251	0.236622	0.236622	0.236172	0.236622
	C4	0.063473	0.063473	0.153090	0.063473	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.090863	0.063473	0.063473	0.060482	0.063473
	C5	0.161250	0.161250	0.142916	0.161250	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.122280	0.161250	0.161250	0.161233	0.161250
	C6	0.043299	0.043299	0.065742	0.043299	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.086526	0.043299	0.043299	0.043078	0.043299
	C7	0.306438	0.306438	0.192984	0.306438	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.219905	0.306438	0.306438	0.304932	0.306438
D Politic	D1	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.000000	0.000000	0.666667	0.666667	0.666667
	D2	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.000000	0.000000	0.333333	0.333333	0.333333
E Modernisation	E1	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.666667	0.000000	0.000000	0.666667
	E2	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.333333	0.000000	0.000000	0.333333

d. Limiting matrix

TABLE 5: Limiting matrix pairwise comparison

		B Economic				C Social							D Politic		E Modernisation		
		B1	B2	B3	B4	C1	C2	C3	C4	C5	C6	C7	D1	D2	E1	E2	goal
B Economic	B1	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092
	B2	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796	0.030796
	B3	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092	0.05092
	B4	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668	0.021668
C Social	C1	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357	0.049357
	C2	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509	0.034509
	C3	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542	0.085542
	C4	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912	0.028912
	C5	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948	0.05948
	C6	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212	0.020212
	C7	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725	0.109725
D Politic	D1	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689	0.101689
	D2	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845	0.050845
E Modernisation	E1	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616	0.203616
	E2	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808	0.101808

TABLE 5: Limiting matrix pairwise comparison
Final weight of the indicator and the rank of sub-indicator

TABLE 6: Final weightage of indicator

Cluster	Indicators	Indicator Weight (local)	Indicator Weight (Global)	Indicator Rank	Sub-Indicator	Sub-Indicator Rank
Economic (E)	Household income (B1)	0.330	0.051	7	<3440	3
					3441-5250	2
					5251-7690	1
					7691-11820	1
					>11820	2
	Insolvency Cases (B2)	0.200	0.031	12	<100	3
					101-400	3
					401-800	2
					>800	1
	Poverty (%) (B3)	0.330	0.051	8	<1.0	4
					1.1-3.0	3
					3.1-15.0	2
					15.1-40.0	2
					>40.0	1

continue...

...cont.

	Income inequality (B4)	0.140	0.022	15	<0.300	3
					0.310-0.350	2
					0.351-0.400	2
					>4.000	1
Social	Mental illness rate (C1)	0.127	0.049	10	<0.108	1
					0.109-0.172	2
					0.173-0.247	3
					0.248-0.462	4
					>0.462	5
	Age (years) (C2)	0.089	0.035	11	<12	4
					13-18	3
					19-39	2
					>40	1
	Radical cases rate (C3)	0.221	0.086	5	<21	1
					22-41	2
					42-71	3
					72-177	4
					>177	5
	Abuse cases (C4)	0.075	0.029	13	<3	1
					4-6	2
					7-11	3
					12-20	4
					>20	5
	Crime cases (C5)	0.153	0.059	6	<107	1
					108-223	2
					224-426	3
					427-813	4
					>813	4
	Population density (C6)	0.052	0.020	14	<50	1
					51-200	2
					201-500	3
					501-1000	4
Politic					>1000	5
	Religion obsession (C7)	0.283	0.110	2	<0.0009	1
					0.001-0.0018	2
					0.0019-0.0041	3
					0.0042-0.0094	4
					>0.0094	5
	Political parties influence (D1)	0.667	0.102	4	Yes	1
					No	2

continue...

...cont.

	Politician influence (D2)	0.333	0.051	9	<5301	1
					5302-14330	2
					14331-27180	3
					27181-67182	4
					>67182	4
	Internet speed (Mbps) (E1)	0.667	0.204	1	<25	1
Modernisation					26-30	1sjo
					31-35	2
					>35	3
	Internet subscription rate (%) (E2)	0.333	0.102	3	<89.60	1
					89.61-93.50	2
					93.51-94.90	3
					94.91-97.3	3
					>97.3	4

Table 2 shows that the consistence index of the ANP is 0.06. This value is acceptable as the acceptable value was less than or equal to 0.1. Table 3 and 4 represent the unweight, weight pairwise comparison value while Table 5 represent the limiting matrix value, which is the final result of the indicator weight. From the result in Table 6, normalise by cluster (local weight) represents the relative importance of an indicator within its cluster while limiting (global weight) reflects the overall importance of and indicator across all clusters. Bar graph in Figure 20 visualise the indicator rank.

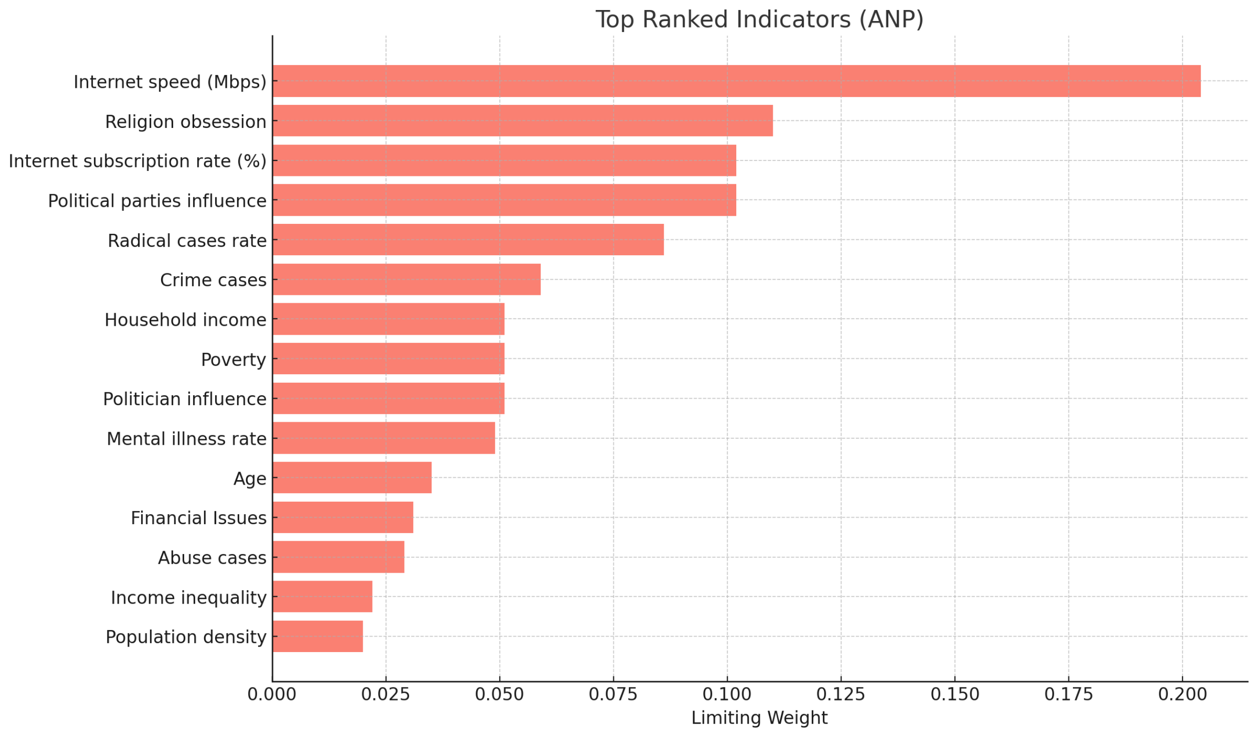


FIGURE 20. Indicator ranked of ANP

Internet speed is the most significant factor among the 15-radicalism susceptibility indicator, at the same time had make it on the first ranking. Follow with religion obsession (0.110) and internet subscription rate (0.102), these are the top three most important indicators. Showing that modernisation indicator seems to be the most influenced indicator as each indicator was placed in top three most important indicators. The least significant indicators are 'abuse cases' (0.029), inequality' (0.022), 'population density' (0.020), and 'financial issues' (0.031). All these indicators fall under the economic and social clusters, with each cluster containing two indicators. The lowest rank of indicators was population density.

Household income and poverty significantly explain local economic influences on radicalism, both with equal importance of 0.330. Globally, their moderate influence in predicting radicalism is reflected in their limiting value of 0.051, indicating that while locally critical, their global impact is indirect.

Social dynamics influencing radicalism are dominated by a social cluster with a weight of 0.388. Within this cluster, religion obsession (0.283) and radical cases rate (0.221) play crucial roles. Religion obsession ranks 2nd globally (0.110), while radical cases rate ranks 5th (0.086), indicating their significant impact on radicalism. Crime cases also show a notable global influence (0.153 local, 0.059 global), ranking 6th. In contrast, age-based indicators (<12, 13–18) contribute minimally. Overall, the social cluster's influence on radicalism is the most pronounced, with religion obsession and radical cases rate being particularly significant.

For political cluter, political parties influence (0.667) dominates this cluster, showing its strong local role in shaping political dynamics. Locally, political parties influence is critical, and it

maintains strong global importance. This suggests that political structures significantly shape the social and economic conditions that lead to radicalism. Internet speed in modernesation cluster, is the most critical factor in predicting radicalism, followed by internet subscription rate. These findings underscore the dual role of modernisation as a driver of radicalisation and a tool for mitigation.

To conclude ANP result, in view of local weight indicators like religion obsession, radical cases rate, and internet speed dominate within their clusters, reflecting their localised influence on radicalism. However, political and economic factors such as political parties influence, and household income are locally important but less dominant compared to social and modernisation factors. while for global weight, internet speed (rank 1, global weight: 0.204) and religion obsession (rank 2, global weight: 0.110) are the most influential globally, indicating the critical role of modernisation and social dynamics in radicalism prediction. Radical cases rate (rank 5, global weight: 0.086) is a direct global measure of radicalism, reinforcing its predictive value.

RADICALISM SUSCEPTIBILITY MAP

The Analytic Network Process (ANP)-derived radicalism susceptibility map in Figure 21 shows a complex risk distribution, with high susceptibility areas primarily located in inland areas such as Gua Musang, Jeli, and Hulu Perak, as well as portions of northern Kedah and Perlis. More districts in central and southern Peninsular Malaysia, including Jempol and Tampin, were found to be at high risk. The ANP's sensitivity to the relationships between socioeconomic, political, and modernisation elements is credited with this change. According to the analysis, socioeconomic differences and the resulting societal pressures make suburban and semi-urban areas.

The northern and southern regions are defined by varying levels of religious obsession, as indicated by the number of mainstream and religious educational institutions. The northern high susceptibility areas, characterised by numerous religious schools, serve as indicators that incite radical thought, leading to rigid ideologies and increased vulnerability to radical behaviour (Troian & Bélanger, 2024).The regions identified as having extremely low and low susceptibility (southern) are linked to places with high mainstream schools that have a low level of religious fixation.

The Analytic Network Process (ANP) is a multi-criteria decision-making methodology that utilises expert judgement to allocate weights to aspects of radicalism. The ANP model yields precise classifications across susceptibility zones, with a proportional distribution among very high, high, moderate, low, and very low categories. This method is esteemed for its capacity to yield clear and succinct outcomes, rendering it an invaluable instrument for decision-makers in GIS contexts. The ANP model dynamically displays susceptibility patterns by capturing complex interactions among indicators. The ANP model enhances the differentiation of susceptible regions by emphasising the influence of systemic factors. The ANP enhances explanatory power and resilience in GIS-based radicalism susceptibility assessment by integrating mutual interactions across criteria, despite increasing model complexity and processing requirements.

The Analytic Network Process (ANP) offers a comprehensive decision-support framework by integrating interdependencies among indicators; yet, its results rely on expert judgement and reflect a static evaluation of a dynamic phenomenon. The approach generates relative susceptibility rankings instead of probabilistic forecasts, and its intricacy may hinder immediate interpretability. However, when bolstered by robustness and comparative analysis, ANP provides significant insights for pinpointing regions with increased susceptibility to radicalism.

The results obtained were not comparable due to the limited number of studies employing the ANP technique in predicting radicalism. Nonetheless, the predictive potential of the ANP approaches cannot be disregarded. Although AHP has been extensively utilised in incidence prediction studies, recent research indicates that ANP produces improved outcomes due to its capacity to capture interrelationships and feedback across variables.

The efficiency of the applied method has been previously demonstrated in many natural disaster incidences (Salleh et al. 2018) while this study initiate a comprehensive study on the application of this method in the context of man-made disasters.

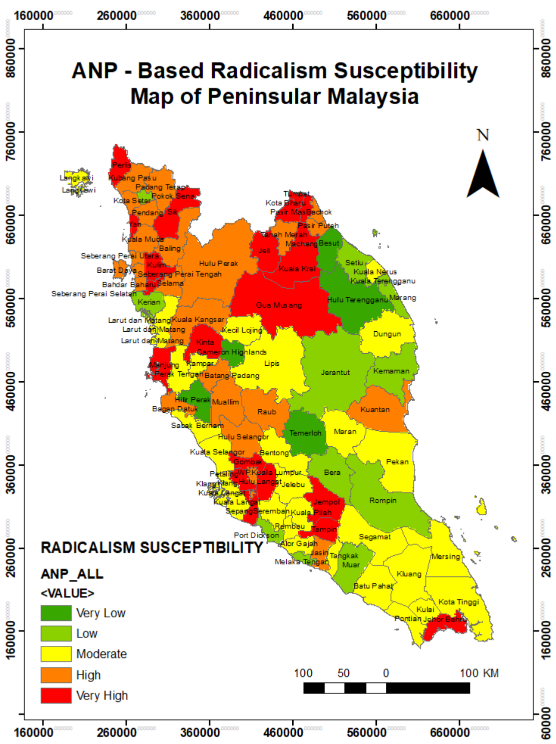


FIGURE 21.Radicalism susceptibility map of Peninsular Malaysia

AUC AND ROC MAP VALIDATION

In the ROC curve in Figure 22 from the area under the curve (AUC), were used to evaluate the efficiency of the models. Evaluation of the models showed that the prediction model using ANP yielded performance coefficients 68%. These values indicate the good performance of the models for radicalism susceptibility assessment in the study area.

ANP's capacity to consider reciprocal interactions and dependencies among criteria enhances the sensitivity of measurement outcomes to indicator variations and improves the accuracy in recognising susceptibility patterns, hence establishing its superiority. The AUC curve value in the ANP model indicates that the ANP is effective in identifying potentially high-risk locations, possibly owing to its capacity to interlink the effects of each signal on others.

The ANP model is a comprehensive technique that allows all direct and indirect factors to influence decision-making. ANP method allows for more complex relationships between decision levels and features to be evaluated because levels do not require a strict hierarchical structure. Because of the interdependence characteristics. It is also important to consider the interrelationships between the criteria in the decision-making (Alilou et al. 2019) and (Kanani-sadat et al. 2019). The ANP method allows user to examine the interdependencies between the criteria levels and is, therefore, an appropriate tool for multi-criteria decision-making (Sun & Cheng 2016).As the AUC value produce is 0.688 the results produce are accepted as the AUCROC value is more that 50% as stated by (Çorbacıoğlu & Aksel 2023).

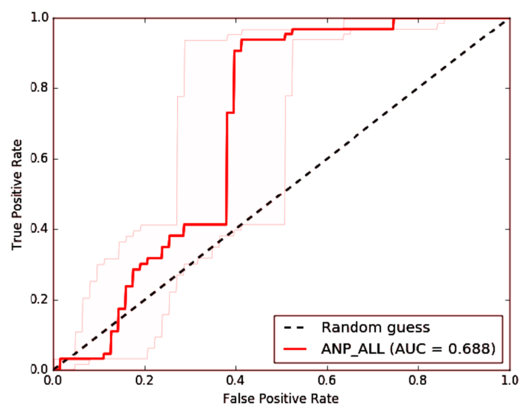


FIGURE 22.AUC-ROC results

CONCLUSION

The studied area has suffered greatly due to the prevalence of extremism. In order to develop effective early preventive strategies, the current study focused on developing radicalism susceptibility maps for the Malaysian Peninsula.

This was achieved by the use of the ANP. An inventory map was first made. 67 regions where radicalism occurred were mapped in this study using historical records and data sets from the Global Terrorism Database (GTD). Fifteen variables were chosen from the four primary clusters of radicalism—economic, social, political, and modernisation—after a comprehensive analysis. An economic cluster is made up of four indicators: poverty, income disparity, bankruptcy cases, and family income. A social cluster is defined by seven indicators: age, the prevalence of radical cases, abuse cases, criminal cases, mental cases, population density, and religious obsession. The modernisation cluster's internet speed and subscriber rate, and the political cluster's political parties and politician influence, are two metrics shared by both the modernising and political clusters. The most significant of these are religious obsession and internet speed. The performance of the approaches was then evaluated using the area under the ROC curve (AUC). AUC values were considered satisfactory. For the benefit of stakeholders and the national safety agency, this study produces radicalism susceptibility maps. Through the implementation of appropriate preventative measures and mitigation processes, they may make informed decisions quickly to protect the most targeted territory and reduce the harm caused by the occurrence of radicalism both now and in the future. Other modernisation and political cluster components should be the focus of future study and model development. Better methods like deep learning and machine learning, like the ANN approach, could be used to make more accurate predictions and produce more reliable results on radicalism susceptibility.

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DECLARATION OF COMPETING INTEREST

None.

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