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IDENTIFYING LEADING HAZARDS IN RIAU ISLANDS: A MONTHLY MARKOV CHAIN ANALYSIS OF DISASTER DOMINANCE PATTERNS

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Abstract. *This study analyzes disaster dominance patterns in the Riau Islands using a monthly Markov chain model with five states: non hazard* (S_0)*, hydrological* (S_1*,flood*)*, geomorphological* (S_2*,landslide*)*, meteorological* (S_3*,extreme weather*)*, and ecological* (S_4*,wildfire*) *hazard. Based on 2019 - 2024 data from Indonesia's National Disaster Management Agency* (*BNPB*)*, the research quantifies transition probabilities between hazard states and computes steady-state distributions to identify long-term risks. Key findings reveal wildfires dominate the system with* 40.6% *steady-state probability and high persistence* (63% *monthly recurrence*)*, reflecting the region's dry-seasonal vulnerability. Extreme weather and floods show significant but secondary prevalence* (24.1% *and 12.5%, respectively*)*. Landslides are rare* (2.5%) *but often escalate to wildfires. The transition matrix highlights wildfire transitions following floods* (44.5% *probability*)*, suggesting delayed risk cascades. Methodologically, this study advances archipelagic hazard modeling by integrating monthly timesteps and hazard taxonomy, offering granular insights for policymakers. Practical implications include prioritizing peatland restoration, flood-resistant infrastructure, and ASEAN-wide early warning systems to address transboundary haze.*

Keywords: Hazard, Markov Chain, Monthly Disaster, Riau Islands.

1. Introduction

The escalating frequency of climate-driven disasters has intensified the need for advanced modeling to enhance risk assessment and preparedness [1,2,3,4]. Markov chain models have emerged as a powerful tool for analyzing temporal disaster patterns [5,6,7,8,9,10], from hydrological to ecological hazards [11,12,13], by quantifying

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transition probabilities between hazard states. While such approaches have been applied in continental regions [14,13,15,16], archipelagic areas (particularly in Southeast Asia) remain understudied despite their unique vulnerability to compound multi-hazards interactions. This study bridges this gap by focusing on the Riau Islands, a province where maritime geography amplifies risks from hydrological, geomorphological, meteorological, and ecological hazards [17,18,19]. Using a monthly Markov chain model, we aim to decode recurrent hazard dominance patterns, analyze inter-hazard transitions dynamics, and develop a predictive framework for coastal resilience.

Comprising over 2400 islands, the Riau Island face multi-hazard threats exacerbated by monsoon systems and coastal ecosystems [20,21,22,23]. Unlike mainland regions [24,25], disaster cascades here often intertwine marine and terrestrial impacts, for instance, extreme rainfall triggering simultaneous hydrological and geomorphological hazards, or dry winds accelerating ecological hazards [26]. Previous Indonesian disaster research has prioritized seismic or annual-scale climate events [27,28,29,30], overlooking monthly hazard dynamics critical for local adaptation. By leveraging a dominant-state Markov chain approach, this study captures how hazard categories dominate each month across six years (2019 - 2024), offering granular insights for policymakers to tailor mitigation to the archipelago's intra-annual hazard rhythms.

Methodologically, we classify monthly disaster data into five states, non-hazard condition (baseline), hydrological hazard (flood), geomorphological hazard (landslide), meteorological hazard (extreme weather), and ecological hazard (wildfire). For months with multi-hazard occurrences, dominance is determined by frequency, supplemented by temporal proximity, a novel adjustment for archipelagic contexts where concurrent hazards are common. The resulting model not only clarifies seasonal hazard transitions but also supports adaptive planning for marine industries and island communities [31,32,33,34]. Beyond the Riau Islands, this framework is scalable to other Southeast Asian archipelagos, advancing regional strategies for multi-hazard resilience.

2. Methods

2.1. *Analytical Framework*

This study adopts a quantitative approach using a finite-state Markov chain model to analyze monthly transition dynamics among four hazard states and a non-hazard state. The methodology is anchored in three theoretical foundations:

(1) State Space Definition
The system is defined by a discrete state space $S = \{S_i\}$ with $i = 0, 1, 2, 3, 4$, classified according to UNDRR hazard taxonomy [35], where S_0 is non-hazard condition (baseline), S_1 is hydrological hazard (flood), S_2 is geomorphological hazard (landslide), S_3 meteorological hazard (extreme weather), and S_4 is ecological hazard (wildfire).

(2) Markov Property

The model follows the memoryless property, where the transition probability to a future state depends solely on the current state [36]:

$$P(X_t = j | X_{t-1} = i, \cdots, X_1 = i_1, X_0 = i_0) = P(X_t = j | X_{t-1} = i).$$

(3) Stationary Transition Probability
Transition probabilities are assumed time-invariant [37]:

$$p_{ij} = P(X_t = j | X_{t-1} = i),$$

where p_{ij} represents the fixed probability of moving from state i to j.

2.2. *Data Acquisition and Preprocessing*

Monthly disaster records (2019 - 2024) were obtained from Indonesia's National Disaster Management Agency (BNPB) [38]. The dataset documented hydrological hazard (flood), geomorphological hazard (landslide), meteorological hazard (extreme weather), and ecological hazard (wildfire) across the Riau Islands. To ensure Markov chain compatibility, the following rules were applied:

(1) Single-Disaster Months
If multiple incidents of one hazard type occurred in a month (e.g., three hydrological hazard events), the month was classified under that hazard state.
(2) Multi-Disaster Months
For months with multiple disaster types, dominance was determined by frequency (the hazard with the highest occurrence count) and temporal proximity (if frequencies were equal, the disaster clustered around mid-month was selected). This approach simplified transition analysis by assigning one dominant state per month.

2.3. *Model Implementation*

The analysis followed a two-phase process to derive transition patterns and long-term trends:

(1) Transition Matrix Estimation
A matrix $P_{5\times5}$ was constructed, where each element p_{ij} represents the monthly transition probability from hazard state i to j:

$$P = \begin{bmatrix} p_{S_0,S_0} & p_{S_0,S_1} & p_{S_0,S_2} & p_{S_0,S_3} & p_{S_0,S_4} \\ p_{S_1,S_0} & p_{S_1,S_1} & p_{S_1,S_2} & p_{S_1,S_3} & p_{S_1,S_4} \\ p_{S_2,S_0} & p_{S_2,S_1} & p_{S_2,S_2} & p_{S_2,S_3} & p_{S_2,S_4} \\ p_{S_3,S_0} & p_{S_3,S_1} & p_{S_3,S_2} & p_{S_3,S_3} & p_{S_3,S_4} \\ p_{S_4,S_0} & p_{S_4,S_1} & p_{S_4,S_2} & p_{S_4,S_3} & p_{S_4,S_4} \end{bmatrix}.$$

Each p_{ij} was calculated as:

$$p_{ij} = \frac{n_{ij}}{\sum_{k=0}^{4} n_{ik}},$$

where n_{ij} counts observed transitions from i to j [39].

(2) Steady-State Analysis
The long-term behavior of the Markov chain was analyzed through n-step transition matrices (P^n), where

$$P^n = P \cdot P \cdot P \cdots P \text{ (matrix multiplied by itself } n \text{ times).}$$

As n approaches infinity ($n \to \infty$), the transition matrix converges to a stationary distribution where each column becomes identical, indicating the system has reached equilibrium. Formally:

$$\lim_{n\to\infty} P^n = \begin{bmatrix} \pi_0 & \pi_1 & \pi_2 & \pi_3 & \pi_4 \\ \pi_0 & \pi_1 & \pi_2 & \pi_3 & \pi_4 \\ \pi_0 & \pi_1 & \pi_2 & \pi_3 & \pi_4 \\ \pi_0 & \pi_1 & \pi_2 & \pi_3 & \pi_4 \\ \pi_0 & \pi_1 & \pi_2 & \pi_3 & \pi_4 \end{bmatrix}.$$

Here, identical columns imply the long-term probability distribution $\boldsymbol{\pi}$ becomes independent of the initial state. The steady-state vector $\boldsymbol{\pi}$ represents the long-term probability of π_0 (non-hazard conditions), π_1 (hydrological hazards), π_2 (geomorphological hazards), π_3 (meteorological hazards), and π_4 (ecological hazards). It was computed by solving:

$$\sum_{j=0}^{4} \pi_j = 1 \text{ and } \pi_j = \sum_{i=0}^{4} \pi_i \cdot p_{ij}.$$

This reveals the proportional likelihood of each state over extended periods, aiding regional risk assessment.

3. Result and Discussion

3.1. *Monthly Transition Results*

The transition probability matrix (Table 1) quantifies monthly hazard state transitions in the Riau Islands during the 2019 - 2024 observation period. These values represent absolute transition frequencies between five defined states, providing empirical evidence of hazard progression patterns. This matrix forms the foundation for understanding both short-term hazard sequence and long-term risk tendencies in this archipelagic region.

Table 1. Hazard Transition Patterns

	Non-Hazard	Hydro logical	Geomorpho logical	Meteoro logical	Eco logical	Total Outflows
Non-Hazard	8	3	1	2	2	16
Hydrological	1	3	0	1	4	9
Geomorphological	0	0	1	0	1	2
Meteorological	3	0	0	10	4	17
Ecological	3	3	0	4	17	27
Total Inflows	15	9	2	17	28	71

Analysis of Table 1 reveals several critical findings regarding monthly hazard dynamics. First, the no-hazard condition demonstrated strong stability (8 transitions to itself), indicating most months remained disaster-free. Second, transitions from non-hazard to flood conditions (3) were more frequent that to other hazards, suggesting hydrological hazards most commonly initiate disaster sequences following calm period.

The transition probability matrix was constructed through systematic normalization of observed frequencies. For each state, we applied maximum likelihood estimation by dividing each transition count by its corresponding row total. For example, transition probabilities from Non-Hazard were calculated as:

$$\begin{aligned}
P(Non-Hazard \to Non-Hazard) &= \tfrac{8}{16} = 0.500,\\
P(Non-Hazard \to Hydrological) &= \tfrac{3}{16} = 0.188,\\
P(Non-Hazard \to Geomorphological) &= \tfrac{1}{16} = 0.062,\\
P(Non-Hazard \to Meteorological) &= \tfrac{2}{16} = 0.125,\\
P(Non-Hazard \to Ecological) &= \tfrac{2}{16} = 0.125.
\end{aligned}$$

This standardization preserves essential Markov properties while generating probability matrix P that characterizes the region's hazard dynamics:

$$P = \begin{bmatrix} 0.500 & 0.188 & 0.062 & 0.125 & 0.125 \\ 0.111 & 0.333 & 0.000 & 0.111 & 0.445 \\ 0.000 & 0.000 & 0.500 & 0.000 & 0.500 \\ 0.177 & 0.000 & 0.000 & 0.588 & 0.235 \\ 0.111 & 0.111 & 0.000 & 0.148 & 0.630 \end{bmatrix}.$$

Figure 1 presents these dynamics visually through a flow diagram, where arrow thickness represents transition probability magnitude.

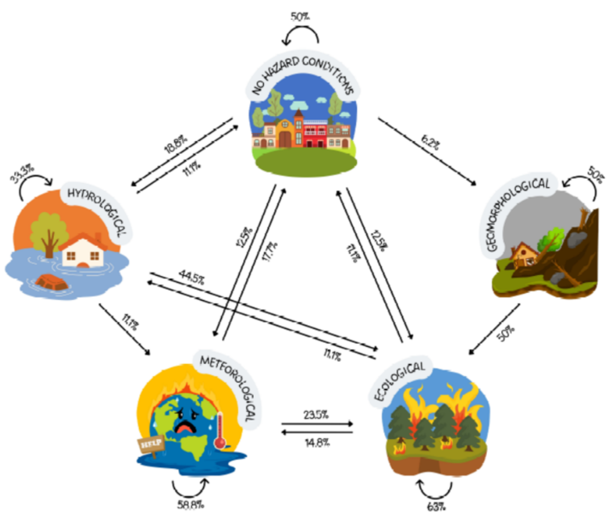

Figure. 1. Hazard Transition Probability Flow Diagram in Riau Islands

Based on Figure 1, the transition probability matrix reveals distinct patterns in monthly hazard dynamics across the Riau Islands. The non-hazard state demonstrates strong persistence (50% probability of remaining), indicating prolonged calm periods. Transitions to hydrological hazards (floods) at 18.8% are more frequent than to geomorphological hazards (landslides) at 6.2%, reflecting the region's vulnerability to hydrological events. This finding aligns with BPS data for 2025, which recorded 8 flood events across the province, with Tanjung Pinang and Natuna regencies experiencing the highest occurrences (3 and 2 events, respectively) [40]. Hydrological hazards exhibit moderate persistence (33.3%) but a notably high transition probability to ecological hazards (44.5%), a pattern that may suggest post-flood conditions to fire risk escalation. This interpretation, however, remains speculative and requires further investigation with higher resolution temporal data. Interestingly, this finding contrasts with Hayati et al. (2026) [41], who reported that most disasters in Riau Islands occur as isolated events rather than consecutive sequences when analyzed daily resolution. The discrepancy may be attributed to the different temporal scales: monthly aggregation may better capture seasonal transition patterns that daily analysis might smooth over.

3.2. *Long-Term Hazard Prevalence*

The long-term behavior of the Markov chain was investigated through n-step transition matrices (P^n), where P^n represents the transition probabilities after n months. As n increases, the system converges to a steady state distribution ($\boldsymbol{\pi}$), where each column of P^n becomes identical, indicating that the probability of being in any given state becomes independent of the initial conditions.

The 2-step transition matrix ($P^2 = P \cdot P$) was computed to assess short-term dependencies, followed by iterative multiplication until P^n stabilized.

$$P^2 = \begin{bmatrix} 0.307 & 0.171 & 0.062 & 0.175 & 0.285 \\ 0.162 & 0.181 & 0.007 & 0.182 & 0.468 \\ 0.056 & 0.055 & 0.250 & 0.074 & 0.565 \\ 0.219 & 0.059 & 0.011 & 0.403 & 0.308 \\ 0.164 & 0.128 & 0.007 & 0.206 & 0.495 \end{bmatrix},$$

$$\vdots$$

$$P^5 = \begin{bmatrix} 0.203 & 0.128 & 0.033 & 0.229 & 0.407 \\ 0.200 & 0.128 & 0.021 & 0.238 & 0.413 \\ 0.173 & 0.119 & 0.045 & 0.211 & 0.452 \\ 0.211 & 0.119 & 0.025 & 0.257 & 0.388 \\ 0.202 & 0.126 & 0.021 & 0.241 & 0.410 \end{bmatrix},$$

$$\vdots$$

$$P^{10} = \begin{bmatrix} 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \\ 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \\ 0.202 & 0.125 & 0.025 & 0.240 & 0.408 \\ 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \\ 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \end{bmatrix}.$$

Clear convergence trend emerges, with columns becoming more uniform. At convergence ($n \to \infty$), P^n reached:

$$P^n = \begin{bmatrix} 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \\ 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \\ 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \\ 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \\ 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \end{bmatrix}.$$

The identical columns of the matrix P^n confirm the stationary distribution $\boldsymbol{\pi} = (0.203, 0.125, 0.025, 0.241, 0.406)$, where each π_j represents the long-term probability of state j. The same distribution was derived algebraically by solving equations:

$$\begin{aligned} \pi_0 &= 0.500\pi_0 + 0.111\pi_1 + 0.000\pi_2 + 0.177\pi_3 + 0.111\pi_4, \\ \pi_1 &= 0.188\pi_0 + 0.333\pi_1 + 0.000\pi_2 + 0.000\pi_3 + 0.111\pi_4, \\ \pi_2 &= 0.062\pi_0 + 0.000\pi_1 + 0.500\pi_2 + 0.000\pi_3 + 0.000\pi_4, \\ \pi_3 &= 0.125\pi_0 + 0.111\pi_1 + 0.000\pi_2 + 0.588\pi_3 + 0.148\pi_4, \\ \pi_4 &= 0.125\pi_0 + 0.445\pi_1 + 0.500\pi_2 + 0.235\pi_3 + 0.630\pi_4. \end{aligned}$$

Subject to the normalization equation: $1 = \pi_0 + \pi_1 + \pi_2 + \pi_3 + \pi_4$.

Using Gaussian elimination, a numerically stable algorithm for linear systems, we computed the steady-state probabilities $\boldsymbol{\pi}$. These values remain invariant when multiplied by the transition matrix, characterizing the long-term distribution of hazard states.

$$\pi = \begin{bmatrix} Non-Hazard & Hydrological & Geomorphological & Meteorological & Ecological \\ 0.203 & 0.125 & 0.025 & 0.241 & 0.406 \end{bmatrix}.$$

For enhanced interpretation of the Markov chain's equilibrium results, Figure 2 employs a pie chart visualization of the steady-state probabilities. This format effectively contrasts the prevalence level among different disaster categories in Riau Island's long-term hazard profile.

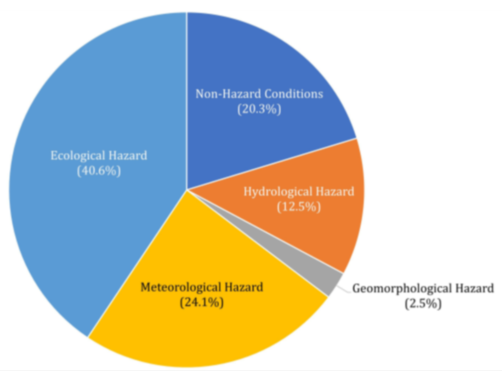

Figure. 2. Long-Term Hazard Prevalence in Riau Islands

Based on Figure 2, the steady-state distribution reveals the long-term hazard prevalence in the Riau Islands, highlighting the region's unique risk profile.

Ecological hazards (wildfires) dominate with a 40.6% probability, reflecting the archipelago's acute vulnerability to prolonged dry seasons and peatland fires. This finding is strongly corroborated by BPS data for 2025, which recorded 75 wildfire events in the Riau Islands (the highest among all disaster types) with Bintan Regency alone accounting for 54 of these events, followed by Natuna with 15 events [40]. Additionally, DIBI 2025 data confirms wildfire occurrences persisting from January through March, with two events in February alone [42].

Furthermore, Hayati et al. (2026) [41] reported a wildfire steady-state probability of 11.2% using daily data for 2024. The higher prevalence in our monthly analysis (40.6%) suggest that monthly aggregation may better capture seasonal wildfire patterns compared to daily scale analysis, which tends to smooth out temporal clustering. This methodological insight underscores the importance of selecting appropriate temporal resolution based on research objectives.

Meteorological hazards (extreme weather) account for 24.1% of steady-state occurrences, underscoring the influence of monsoonal winds and tropical storms on regional disaster risks. BPS 2025 data substantiates this finding with 22 extreme weather events recorded across the province, with Batam City experiencing the highest frequency (9 events), followed by Karimun (6 events) [40]. Hayati et al. (2026) [41] similarly identified extreme weather as the second most persistent hazard after wildfires, reinforcing the consistency of these findings across different analytical approaches.

Hydrological hazards (floods) show moderate prevalence (12.5%), consistent with the region's exposure to coastal inundation and river overflow during peak rainfall. BPS data recorded 8 flood events in 2025, with Tanjung Pinang (3 events), Natuna (2 events), Bintan (1 event), Lingga (1 event), and Batam (1 event). Notably, DIBI 2025 data indicates flood events occurring in August and December, suggesting a seasonal pattern that aligns with the monsoon cycle.

Geomorphological hazards (landslides) are the rarest (2.5%), as their occurrence depends on localized triggers like steep slopes combined with extreme precipitation. BPS 2025 data confirms only 3 landslide events, all occurring in Batam City [40]. DIBI 2025 records one landslide event in January [42], supporting the model's indication of very low long-term prevalence. This finding is consistent with Hayati et al. (2026) [41], who reported a 0.3% steady-state probability for landslides in their daily analysis.

3.3. *Early Warning Systems and Policy Recommendations*

3.3.1. *Early Warning Systems Optimization*

Given that ecological hazards dominate with $\pi_4 = 40.6\%$ steady-state probability and demonstrate the highest persistence ($P_{44} = 0.630$), investments in real time satellite monitoring (e.g., MODIS, VIIRS) and community-based fire alert systems are essential. Predictive models should integrate weather data (e.g., wind speed, drought indices) to anticipate outbreaks, particularly in Bintan and Natuna regencies, which recorded the highest wildfire frequencies in 2025 (54 and 15 events, respectively) [40].

The high prevalence of meteorological hazards ($\pi_3 = 24.1\%$) calls for localized storm forecasting and marine weather advisories to protect fisheries and coastal infrastructure. Given that BPS 2025 data recorded 22 extreme weather events, with Batam City (9 events) and Karimun (6 events) being most affected, early warning systems should prioritize these high risk districts.

Despite moderate prevalence ($\pi_1 = 12.5\%$), the significant flood to wildfire transition probability ($P_{14} = 0.445$) suggests that flood warnings should be integrated with fire risk assessments. Installing IoT enabled water level monitors in flood prone rivers (particularly in Tanjung Pinang and Natuna) linked to SMS alerts for coastal communities is recommended.

3.3.2. *Evidence Based Policy Recommendations*

Given that wildfires account for 40.6% of long-term hazard prevalence, approximately 40% of the annual disaster mitigation budget should be allocated to wildfire prevention, including peatland restoration, community fire brigades, and satellite based early warning systems. This prioritization is justified by the high persistence probability ($P_{44} = 0.630$) and is consistent with BNPB's 2025 data showing wildfires as the most frequent hazard in the region [42].

Based on the transition probability analysis indicating that $P_{01} = 0.188$ (non-hazard to flood) and $P_{04} = 0.125$ (non-hazard to wildfire), restrict agricultural burning during dry seasons (June-September) when fire persistence is highest. Enforce building codes for extreme wind or rain in regions with high meteorological hazard probability ($\pi_3 = 0.241$), particularly in Batam City and Karimun.

Given the 12.5% steady-state probability for hydrological hazards, prioritize flood-resistant infrastructure in hydrological hazard zones, such as elevated roads and drainage systems. Target areas with recurrent flood events identified in BPS 2025 data, with Tanjung Pinang (3 events) and Natuna (2 events) [40].

Leverage the 20.3% non-hazard probability for proactive resilience building. Conduct regular drills for wildfire response and flood evacuation during calm periods, as recommended by Hayati et al. (2026) [41], who emphasized the importance of utilizing non-disaster days for capacity building.

Given the transboundary nature of wildfire haze, partner with neighboring Malaysia and Singapore to address transboundary haze, aligning with ASEAN's Agreement on Transboundary Haze Pollution. This is particularly relevant given Riau Islands' proximity to international borders and the potential for cross-border impacts.

These recommendations align with Indonesia's Disaster Management Law No. 27 [33] and Sendai Framework for Disaster Risk Reduction [34], particularly its emphasis on evidence-based, context-specific risk reduction strategies. The Markov model's quantification of transition probabilities and steady-state distributions provides scientific foundation for prioritizing interventions while maintaining preparedness for other hazards, enabling efficient use of limited resources in this strategically important economic region.

4. Conclusion

This study employed a monthly Markov chain model to analyze disaster dominance patterns in the Riau Islands from 2019 to 2024, focusing on five states: non-hazard, hydrological (flood), geomorphological (landslide), meteorological (extreme weather), and ecological (wildfire) hazards. The key findings reveal distinct transition dynamics and long-term hazard prevalence, offering critical insights for disaster risk reduction strategies in archipelagic regions. The transition probability matrix highlighted strong persistence in ecological hazards (wildfires), with a 63% probability of recurring monthly. Hydrological hazards (floods) showed a 44.5% chance of transitioning to wildfires, suggesting a delayed risk escalation following wet periods. The long-term equilibrium analysis revealed ecological hazards (wildfires) as the most prevalent hazard (40.6%). Meteorological hazards (extreme weather) at 24.1% and hydrological hazards (floods) at 12.5% represent secondary but significant risks. Geomorphological hazards (landslide) ar 2.5% are the rarest. Non-hazard periods (20.3%) occupied a smaller proportion than expected, emphasizing the archipelago's constant exposure to climate-driven threats. Policy recommendations derived directly from our analytical results include allocating approximately 40% of disaster mitigation budgets to wildfire prevention, developing integrated early warning systems that consider the flood-to-wildfire transition, investing in localized extreme weather forecasting, implementing targeted flood mitigation infrastructure, and strengthening regional cooperation with Malaysia and Singapore to address transboundary haze. Future research should integrate climate variables to assess transition probability shifts under climate change scenarios, explore higher-order Markov models to capture multi-month hazard dependencies, and expand spatial resolution to district-level analysis.

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