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Seasonal Variability and Transition Dynamics of Temperature and Windspeed Regimes in Southwestern Nigeria

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ABSTRACT

This study investigated the seasonal variability and transition dynamics of temperature and windspeed regimes in South-west, Nigeria using Fuzzy Markov Model. Daily Temperature and Windspeed data for the South-west States (Lagos, Osun, Ogun, Ondo, Ekiti and Oyo) in Nigeria from 1991 to 2020 (30 years) was obtained from National Aeronautic and Space Administration (NASA) meteorological center. Atmospheric variables often exhibit uncertainty, gradual transitions, and overlapping climatic states that cannot be adequately represented using conventional deterministic classification methods. To address this limitation, fuzzy logic was employed to quantify the degree of belonging of temperature and windspeed conditions to different atmospheric regimes, while transition structures were analysed using fuzzy transition matrices. The climatic variables were categorized into Low/Moderate/High windspeed regimes and Cool/Normal/Hot temperature regimes. The Markov Chain Model result reveals that the high diagonal temperature and windspeed transition probabilities (0.96–0.99) across the South-west regions are highly persistent, with limited switching between regimes while the Fuzzy Model transition analysis (0.77–0.88) of temperature and windspeed across study area reveals strong overlapping atmospheric behaviour during the dry and wet seasons. This implies that climatic conditions do not exist as rigid or isolated states but instead possess varying degrees of belonging to multiple regimes simultaneously. The total elimination of moderate regimes in the Fuzzy transition temperature and windspeed matrices, where the moderate rows had zero membership values, was one of the study's key conclusions. This implies that the South-west climate system has weak, unstable, or transient intermediate atmospheric conditions. The fuzzy logic captured gradual regime transitions and overlapping state memberships that were not evident in the classical Markov framework.

Keywords:
Fuzzy Logic,
Windspeed Variability,
Temperature Regimes,
Degree of Belonging,
Fuzzy Membership Matrix,
Southwest Climate Variability.

INTRODUCTION

Climate variability is a critical environmental challenge in tropical urban regions due to its impacts on atmospheric stability, thermal comfort, and renewable energy potential. Key meteorological variables such as temperature and wind speed exhibit continuous variability driven by solar radiation, moisture transport, cloud dynamics, urbanization, and large-scale atmospheric circulation processes (Barry & Chorley, 2010; IPCC, 2023). Southwestern Nigeria has experienced increasing temperatures, rapid urbanization, changing rainfall characteristics, and increasing frequency of heat-related events over recent decades. Coastal cities such as Lagos are particularly vulnerable because of urban heat-island effects, population growth, and exposure to climate variability associated with the Atlantic Ocean. Observed warming trends across southern Nigeria have raised concerns regarding thermal comfort, energy demand, agriculture, and environmental sustainability (IPCC, 2023; Amadi et al., 2014; Adeniyi, 2020).

Traditional statistical approaches typically discretise atmospheric variables into rigid classes such as cool, normal, and hot temperatures or low, moderate, and high wind speeds. However, atmospheric processes are inherently continuous, and climatic states often overlap rather than exist as mutually exclusive categories. This limitation has motivated the adoption of fuzzy logic methods in environmental and atmospheric sciences.

Fuzzy set theory allows variables to possess partial membership in multiple states simultaneously, providing a more realistic representation of climatic uncertainty and gradual transitions (Zadeh, 1965; Zimmermann, 2010). Applications of fuzzy approaches in climate classification, hydrology, and environmental modelling have demonstrated improved performance in capturing uncertainty and non-linearity compared to classical methods (Ross, 2010). In parallel, Markov-based models, particularly Hidden Markov Models (HMMs), have been widely applied to climate time-series analysis due to their ability to represent systems governed by hidden states and stochastic transitions (Agada et al., 2026; Charles et al., 2004; Agada and Adah, 2026). The foundational work of Rabiner (1989) established HMMs as effective tools for modelling sequential data, while subsequent applications in climatology have demonstrated their utility in identifying regime persistence and transition dynamics (Wilks, 2019; Kemeny & Snell, 1976).

Despite growing applications of statistical and stochastic models in climate studies, limited research in Nigeria has integrated fuzzy logic with regime-switching frameworks to explicitly characterize overlapping atmospheric states and transition behaviour of temperature and wind speed. Several studies on temperature and windspeed emphasize trend detection and descriptive statistics, with insufficient consideration of uncertainty and gradual state transitions in tropical urban climates (Ewona and Udo, 2008; Amadi et al., 2014; Adeniyi, 2020; Agada et al., 2023; Adekoya & Adewale 1992; Adaramola & Oyewola, 2011; Fadare, 2010; Ojosu & Salawu, 1990; Oyedepo et al., 2012). Therefore, this study applies a fuzzy transition modelling framework to investigate the persistence, overlap, and seasonal dynamics of temperature and wind speed regimes in South-west, Nigeria. The approach provides a more flexible representation of atmospheric variability, capturing both stochastic transitions and fuzzy state membership, thereby improving the characterization of complex tropical climate dynamics.

MATERIALS AND METHODS

This research adopts a quantitative stochastic modelling approach to investigating the seasonal variability and transition dynamics of temperature and windspeed regimes in South-west A fuzzy Markov chain model is used to analyse the transitions between climatic states (cool, moderate, and hot). The model is appropriate because atmospheric variables exhibit randomness, temporal dependence, and uncertainty in state classification. A fuzzy model is based on degrees of membership rather than strict probabilities (Zadeh, 1965).

Study Area and Source of Data

South-west Nigeria lies within longitude 20.48' – 60.0' E and latitude 50.5' – 90.12'N. It comprises six states — Ekiti, Lagos, Ogun, Ondo, Osun, and Oyo. The zone stretches along the Atlantic seaboard from the international border with Benin Republic in the west to the South-South in the east with the North Central to the north. The South-West is split with the Central African mangroves in the coastal far south while the major inland ecoregions are the Nigerian lowland forests ecoregion in the south and east along with the Guinean forest–savanna mosaic ecoregion in the drier northwest. The weather conditions vary between Nigeria's two, distinctive seasons; the rainy season (March - November) and the dry season named the Harmattan (from November - February). The Harmattan is a dry and dusty northeasterly trade wind (of the same name), which blows from the Sahara over West Africa into the Gulf of Guinea. During this season, the wind transports the eponymous *Harmattan dust*, particles of fine Saharan sand (Adeniyi, 2018). Daily temperature and wind speed data for the six southwest states were obtained from the NASA Prediction of Worldwide Energy Resources (POWER) Project database through the POWER Data Access Viewer (https://power.larc.nasa.gov/).

Figure 1: Map South-West States in Nigeria

Data Preprocessing and Fuzzy Classification

Daily temperature and wind speed observations were classified into three fuzzy climatic states. For temperature, the states were defined as Cool, Normal, and Hot, while for wind speed the states were defined as Low, Moderate, and High. The fuzzy classification was based on the empirical 30th percentile (Q30) and 70th percentile (Q70) of each variable. Unlike classical classification methods that assign each observation to a single category, fuzzy classification allows observations to possess partial membership in multiple states simultaneously, thereby representing uncertainty and gradual transitions in atmospheric conditions (Zadeh, 1965; Ross, 2010; Zimmermann, 2010). For an observed climatic variable x, the lower-state membership function (Cool for temperature or Low for wind speed) was defined as:

$$\mu_L(x) = \begin{cases} 1, & x \leq Q_{30} \\ \frac{Q_{70}-x}{Q_{70}-Q_{30}}, & Q_{30} < x < Q_{70} \\ 0, & x \geq Q_{70} \end{cases} \quad (1)$$

The upper-state membership function (Hot for temperature or High for wind speed) was defined as:

$$\mu_H(x) = \begin{cases} 0, & x \leq Q_{30} \\ \frac{x-Q_{30}}{Q_{70}-Q_{30}}, & Q_{30} < x < Q_{70} \\ 1, & x \geq Q_{70} \end{cases} \quad (2)$$

The intermediate-state membership function (Normal for temperature or Moderate for wind speed) was computed as:

$$\mu_M(x) = 1 - \mu_L(x) - \mu_H(x) \quad (3)$$

Where: x is the observed temperature (°C) or wind speed (m s^{-1}), Q_{30} is the 30th percentile of the variable, Q_{70} is the 70th percentile of the variable, $\mu_L(x)$, $\mu_M(x)$, and $\mu_H(x)$ are the membership degrees associated with the lower, intermediate, and upper climatic states, respectively.

Membership values range from 0 to 1, where 0 indicates no membership and 1 indicates complete membership in a particular state. This percentile-based fuzzy classification permits smooth transitions between climatic regimes and captures overlapping atmospheric conditions that cannot be represented adequately using crisp-state classification approaches (Ross, 2010; Zimmermann, 2010). Each observation retained its complete fuzzy membership vector, and the fuzzy transition matrices were estimated directly from these membership values rather than assigning observations to a single dominant climatic state. The fuzzy transition matrix was estimated using the outer product of consecutive fuzzy membership vectors. Let:

$$v_t = \begin{bmatrix} \mu_1(t) \\ \mu_2(t) \\ \mu_3(t) \end{bmatrix} \quad (4)$$

Represent the fuzzy membership vector at time t, where $\mu_i(t)$ denotes the degree of membership of the observation to climatic state i.

The fuzzy transition accumulation matrix was computed as:

$$M = \sum_{t=1}^{n-1} v_t \, v_{t+1}^T \quad (5)$$

Where n is the total number of observations and v_{t+1}^T is the transpose of the membership vector at time $t+1$.

The fuzzy transition probability matrix was then obtained through row normalization:

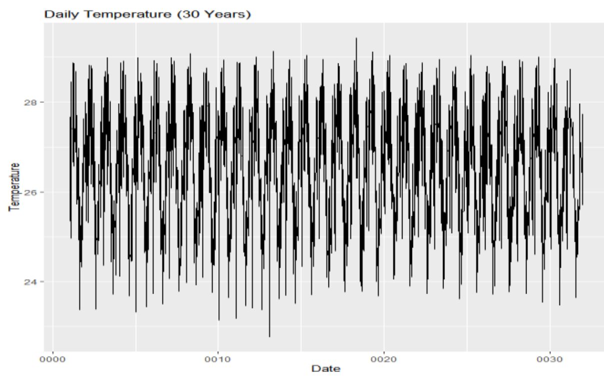
$$P_{ij} = \frac{M_{ij}}{\sum_{j=1}^{k} M_{ij}} \quad (6)$$

Where: P_{ij} represents the fuzzy transition probability from state i to state j, M_{ij} represents the accumulated fuzzy transition weight, and $k = 3$ is the total number of climatic states.

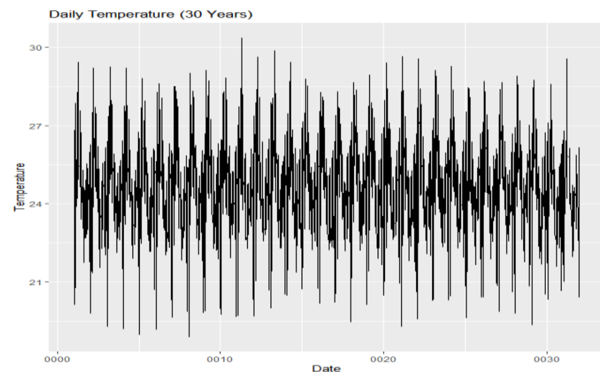
This approach preserves partial memberships and captures gradual transitions between atmospheric regimes, making it particularly suitable for climatic systems characterized by uncertainty and overlapping states (Chen, 2006; Ross, 2010). The resulting matrix is constructed separately for Temperature and Wind speed (wet season was defined as April–October and the dry season as November–March) for each study location.

RESULTS AND DISCUSSION

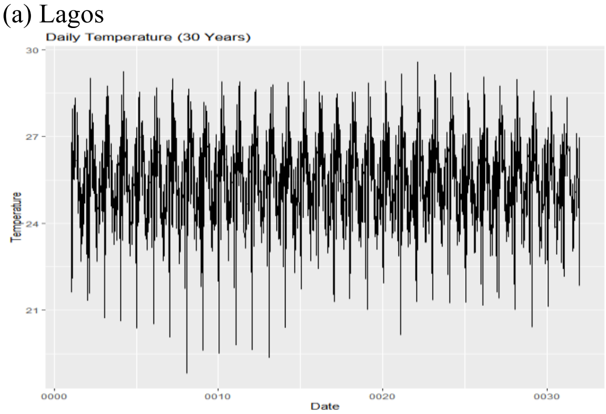
The recurring oscillations in temperature show continuous changes in atmospheric energy balance as presented in Figure 2. Periods of higher temperature correspond to stronger solar heating and reduced cloud cover, which increase surface warming, whereas lower temperature dips may be associated with increased atmospheric mixing, moisture availability, or transient circulation changes that promote cooling. These instabilities are important because temperature is a primary driver of atmospheric circulation. Differential heating between the Earth's surface and the atmosphere generates pressure gradients that control airflow and wind formation (Barry & Chorley, 2010). Thus, even though Figure 2 displays no pronounced long-term upward trend, the persistent variability signals active atmospheric circulation processes influencing local climate conditions. The concentration of temperature values in the upper range (approximately 26–29°C) suggests a consistently warm environment that may be enhanced by urban heat island effects. Heat is retained by urban surfaces like concrete and asphalt, which raises baseline temperatures and decreases nighttime cooling (Oke, 1982). According to IPCC, (2023), increasing temperatures and more recurrent heat extremes are among the most evident indicators of ongoing climate change, particularly in areas where land-use change and urbanization amplify thermal retention. This temporal structure supports the application of fuzzy Markov chain models for capturing temperature-state persistence and transition dynamics under changing atmospheric conditions, as such models are well appropriate for representing uncertainty and slow transitions in climatic systems (Zadeh, 1965; Kosko, 1992).



(a) Lagos



(b) Osun



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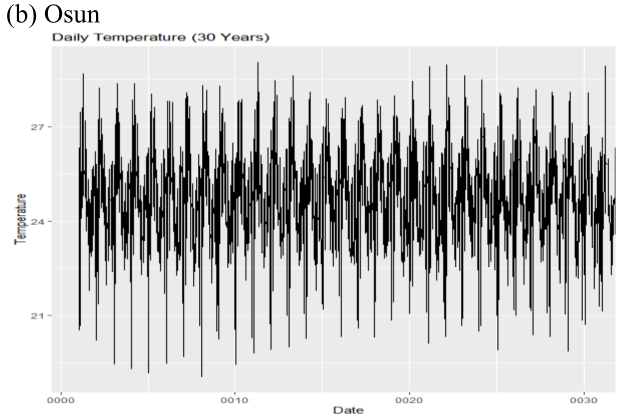
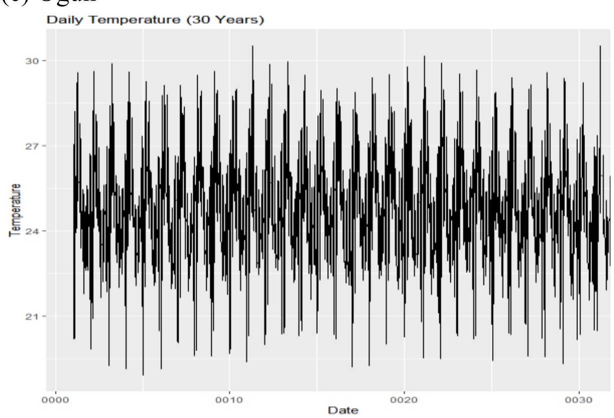
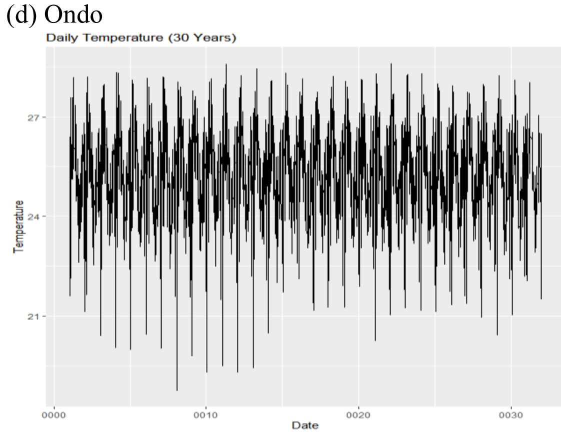


(d) Ondo



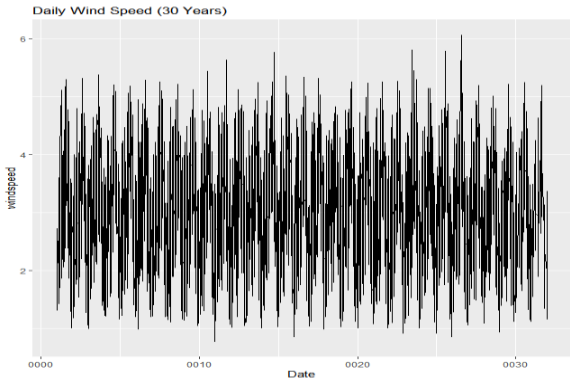
(e) Ekiti



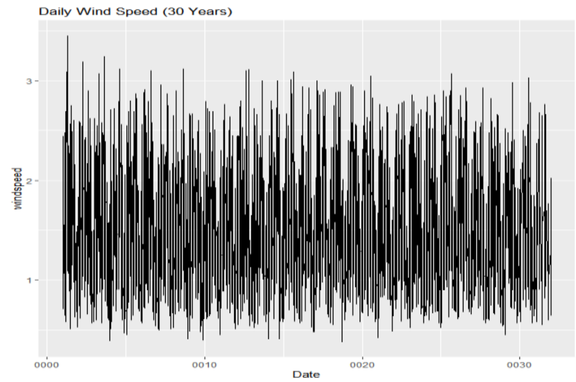
(f) Oyo

Figure 2: Daily Temperature across the South-West States in Nigeria

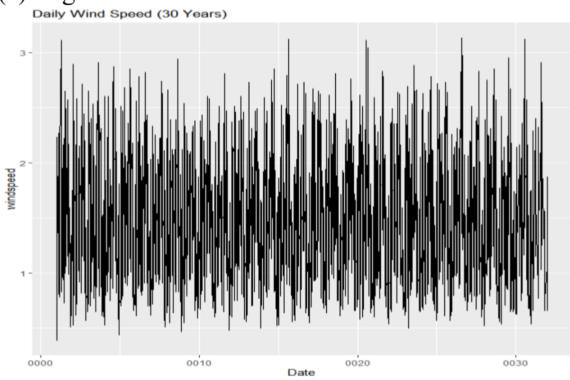
The uneven fluctuations observed in Figure 3 specify continuous adjustments in pressure systems and thermal gradients. Periods of higher wind speed suggest stronger pressure differences and enhanced atmospheric mixing, while lower wind speeds reflect weaker gradients and more stable atmospheric conditions. Wind is fundamentally driven by horizontal pressure-gradient forces arising from differential heating of the Earth's surface and atmosphere (Ahrens & Henson, 2019; Barry & Chorley, 2010). The absence of a clear long-term trend suggests that wind speed variability is dominated more by short-term atmospheric processes and synoptic-scale weather systems than by gradual climatic shifts. However, the repeated oscillations between low and high wind speeds justify the use of a stochastic framework such as the fuzzy Markov chain model to capture state transitions and persistence characteristics.



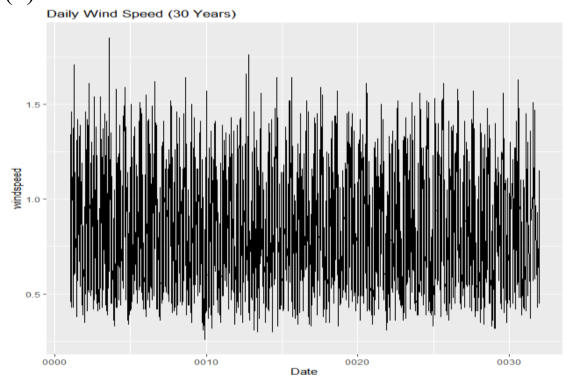
(a) Lagos



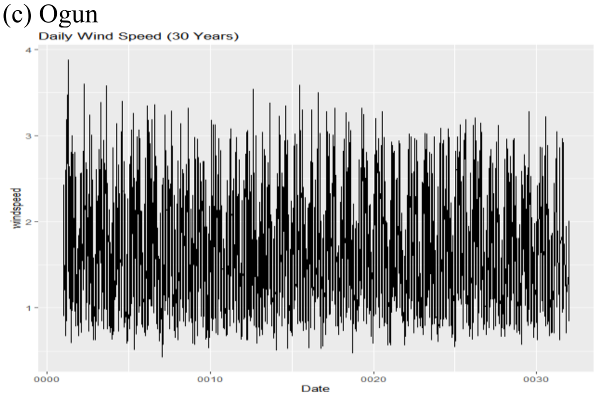
(b) Osun



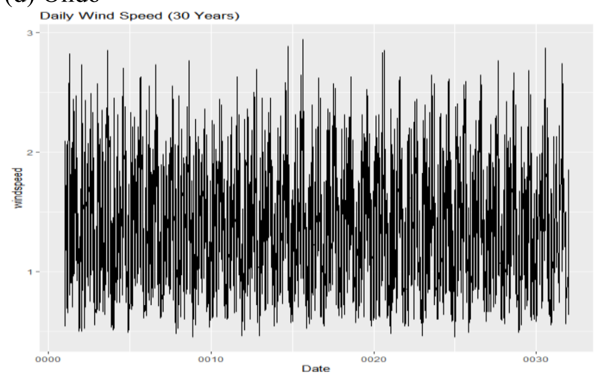
(c) Ogun



(d) Ondo



(e) Ekiti



(f) Oyo

Figure 3: Daily Wind Speed across the South-West States in Nigeria

The Cool, Normal and Hot states exhibit exceptionally high diagonal probabilities (0.96–0.99), indicating strong regime persistence for temperature as presented in Table 1. In Lagos, the Cool-to-Cool (0.97), Normal-to-Normal (0.99), and Hot-to-Hot (0.97) transition probabilities show that once a temperature regime is established, it is highly likely to persist in that state for a while. The strong persistence of thermal regimes is consistent with Amadi et al. (2014), who reported sustained temperature variability across Nigeria. In Markov chain analysis, high diagonal transition probabilities are generally interpreted as evidence of strong state persistence and temporal stability, whereas low off-diagonal probabilities indicate infrequent transitions between states (Norris, 1998; Kemeny & Snell, 1976). The low off-diagonal probabilities observed across the states therefore suggest minimal transitions between thermal regimes, reflecting relatively stable atmospheric conditions and the moderating influence of maritime air masses from the Atlantic Ocean, particularly in coastal locations such as Lagos (Barry & Chorley, 2010). Among the states, Ondo and Ekiti show the highest persistence of cool conditions (0.99), suggesting highly stable cool-temperature regimes. This stability may be associated with vegetation cover, local topographic influences, and moisture availability, which are known to moderate surface temperatures and reduce thermal variability (Geiger et al., 2009).

The persistence of hot conditions is highest in Osun and Ekiti (0.99), indicating that once hot conditions occur, they tend to remain dominant. Such persistence may be indicative of sustained atmospheric heating and prolonged thermal stress, conditions that are expected to become more frequent under a warming climate (IPCC, 2023). Conversely, the slightly lower Hot to Hot probabilities in Ogun and Oyo (0.96) indicate marginally greater thermal variability and a higher likelihood of transitions between thermal states. Overall, the temperature transition matrices demonstrate that thermal regimes across Southwestern Nigeria are highly persistent, with limited switching between cool, normal, and hot states. This pattern is characteristic of climates exhibiting strong temporal autocorrelation and well-defined seasonal thermal structures, where current atmospheric conditions strongly influence future states (Wilks, 2019).

Table 1: Transition Probabilities of Temperature and Wind Speed Regime across Location

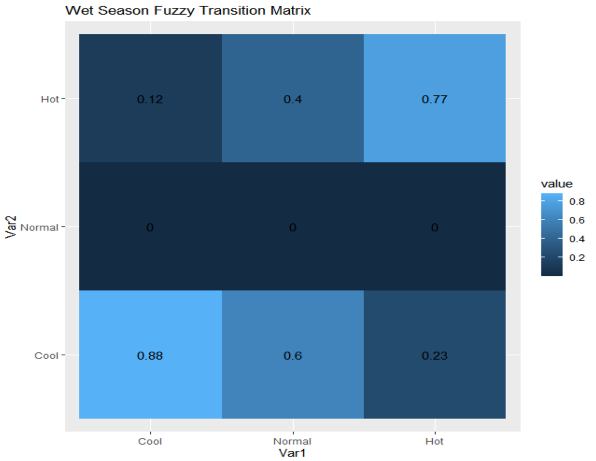
Location	Regime	Temperature			Regime	Wind Speed		
		Cool	Normal	Hot		Low	Moderate	High
Lagos	Cool	0.97	0.00	0.03	Low	0.99	0.01	0.00
	Normal	0.00	0.99	0.01	Moderate	0.01	0.98	0.01
	Hot	0.02	0.01	0.97	High	0.00	0.01	0.99
Osun	Cool	0.97	0.02	0.01	Low	0.78	0.00	0.22
	Normal	0.04	0.96	0.00	Moderate	0.00	0.99	0.01
	Hot	0.00	0.01	0.99	High	0.27	0.02	0.71
Ogun	Cool	0.98	0.01	0.01	Low	0.98	0.00	0.02
	Normal	0.00	0.96	0.04	Moderate	0.00	0.97	0.03
	Hot	0.02	0.02	0.96	High	0.01	0.01	0.98
Ondo	Cool	0.99	0.01	0.00	Low	0.97	0.03	0.00
	Normal	0.00	0.96	0.04	Moderate	0.01	0.98	0.01
	Hot	0.01	0.02	0.97	High	0.00	0.04	0.96
Ekiti	Cool	0.99	0.00	0.01	Low	0.73	0.02	0.25
	Normal	0.00	0.99	0.01	Moderate	0.00	0.99	0.01
	Hot	0.00	0.01	0.99	High	0.18	0.00	0.82
Oyo	Cool	0.97	0.01	0.02	Low	0.98	0.00	0.02
	Normal	0.00	0.97	0.03	Moderate	0.00	0.97	0.03
	Hot	0.02	0.02	0.96	High	0.01	0.01	0.98

The wind speed transition probabilities also reveal strong persistence, although greater variability exists compared with temperature (Table 1). In Lagos, wind speed exhibits near perfect persistence, with Low to Low (0.99), Moderate to Moderate (0.98), and High to High (0.99). The dominance of low to low and high to high wind transitions agrees with Oyedepo et al. (2012), who found strong seasonal dependence of wind energy resources in southern Nigeria. In Markov chain analysis, such high diagonal probabilities indicate strong state persistence and temporal dependence, implying that the current atmospheric state strongly influences future conditions (Norris, 1998; Wilks, 2019). These values suggest an exceptionally stable wind regime in Lagos, where atmospheric circulation patterns are highly sustained over time. The coastal location of Lagos likely contributes to this stability through the influence of sea-breeze circulations, maritime air masses, and the West African monsoon system, which regulate local wind conditions (Nicholson, 2013). Similar patterns are observed in Ogun, Ondo, and Oyo States, where low and high wind regimes exhibit persistence values between 0.96 and 0.98. The persistence of wind regimes observed in this study is consistent with Fadare (2010), who reported relatively stable wind characteristics across southern Nigeria. These high probabilities indicate that wind conditions remain largely within their established regimes and are therefore relatively predictable. However, Osun and Ekiti display lower persistence values, indicating greater wind speed variability and a higher likelihood of transitions between wind regimes. Despite these differences, moderate wind regimes remain highly persistent across all states, with probabilities ranging from 0.97 to 0.99. This suggests that once moderate wind conditions develop, they tend to remain stable.

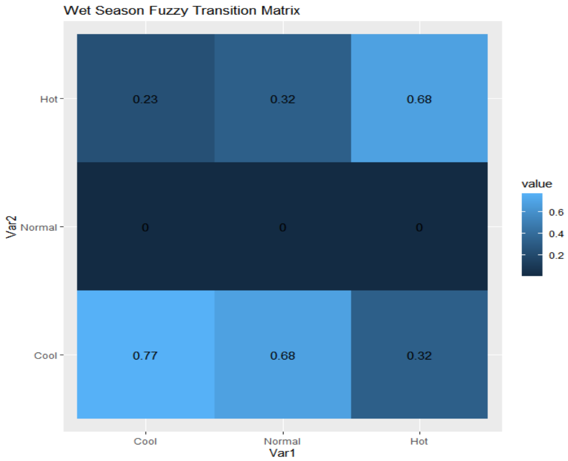
Overall, the transition probability matrices demonstrate that climatic regimes across Southwestern Nigeria exhibit substantial persistence. Temperature states show very strong stability, while wind speed regimes also display considerable persistence, albeit with greater variability in Osun and Ekiti. These findings indicate strong regime memory, whereby present atmospheric conditions exert a significant influence on future states (Kemeny & Snell, 1976; Wilks, 2019). Although the Markov transition matrices revealed strong persistence of temperature and wind speed regimes across Southwestern Nigeria, the classical Markov framework assumes that each observation belongs exclusively to a single climatic state at any given time. However, meteorological variables are inherently continuous and often exhibit overlapping characteristics between adjacent regimes. Consequently, integrating fuzzy logic with the Markov framework provides a more realistic representation of atmospheric processes. The Fuzzy Markov Model enables climatic states to possess varying degrees of membership while simultaneously modelling temporal transitions and persistence behaviour. This approach is particularly suitable for climatic and environmental systems characterized by uncertainty, nonlinearity, and gradual transitions (Kosko, 1992; Chen, 2006). Such characteristics are especially common in tropical environments, where atmospheric conditions rarely exhibit sharply defined boundaries.

The fuzzy wet and dry season matrices demonstrate that temperature and wind speed conditions across Southwestern Nigeria are highly overlapping and continuous (Figures 4-7). This overlap reflects the gradual nature of atmospheric variability in tropical environments, where climatic states are not completely isolated but instead share characteristics with neighbouring regimes. The strong Cool to Cool membership values of 0.88, 0.77, 0.80, 0.77, 0.77, and 0.79 in Lagos, Osun, Ogun, Ondo, Ekiti, and Oyo, respectively, indicate that cool atmospheric conditions are highly dominant and persistent during the wet season (Figure 4). Such persistence is consistent with the influence of increased cloud cover, high humidity, rainfall activity, and reduced incoming solar radiation, all of which contribute to lower surface temperatures during the rainy season (Barry & Chorley, 2010; Nicholson, 2018).

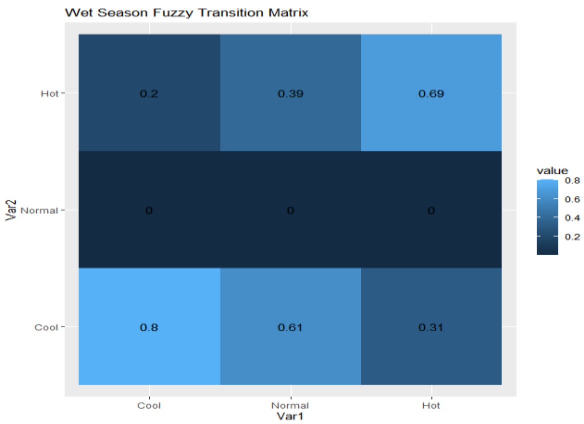
The fuzzy membership values for the wet season ranges from 0.77–0.88, 0.57–0.68, and 0.23–0.33 in the cool state row indicate varying degrees of thermal association between cool, normal, and hot temperature regimes. These values quantify the extent to which atmospheric conditions classified as cool also share characteristics of normal and hot conditions (Zadeh, 1965). The results suggest that wet season temperatures are not exclusively cool but fluctuate between cool and moderately warm conditions. The relatively low memberships associated with the hot regime (23–33%) implies occasional influences of warming processes, possibly arising from intermittent sunshine, urban heat retention, or temporary breaks in rainfall activity. Such overlap is characteristic of tropical climates, where atmospheric transitions generally occur gradually rather than abruptly (Geiger et al., 2009). Unlike probability matrices, fuzzy membership matrices are not constrained to sum to unity because they represent degrees of similarity or association rather than probabilities of occurrence (Zimmermann, 2010). Consequently, a temperature condition during the wet season may simultaneously exhibit strong membership in the cool regime, moderate membership in the normal regime, and weak membership in the hot regime, thereby providing a more realistic representation of climatic variability and transitional atmospheric behaviour.

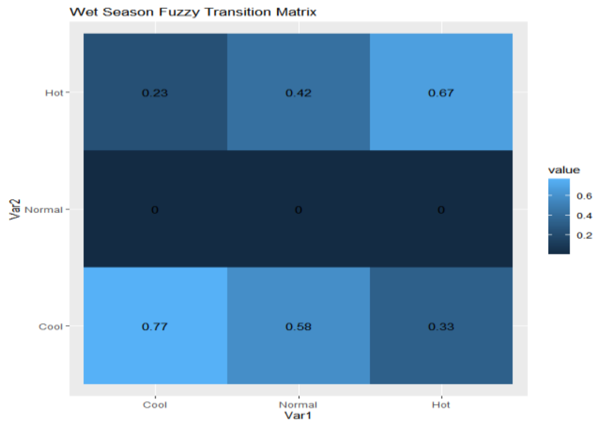


(a) Lagos

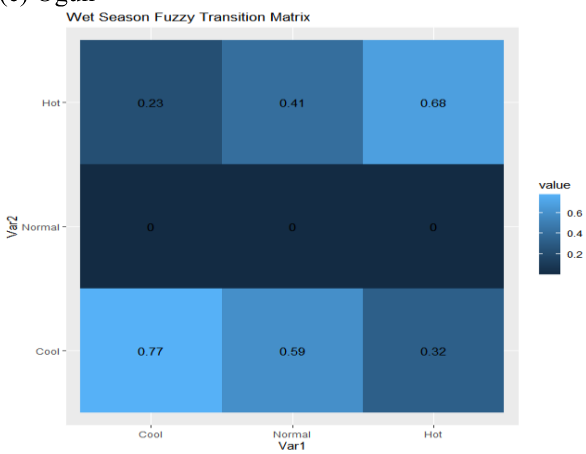


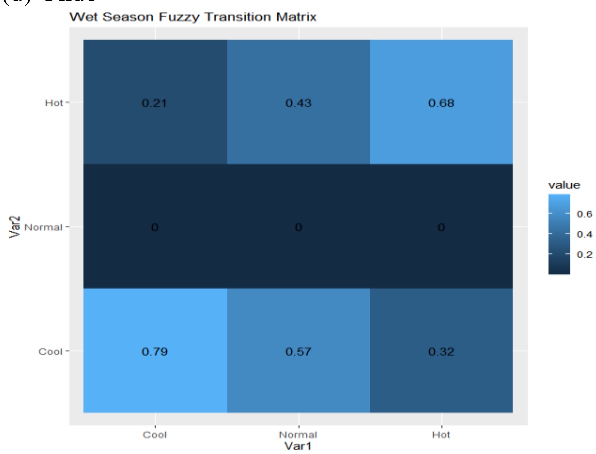
(b) Osun





(c) Ogun (d) Ondo



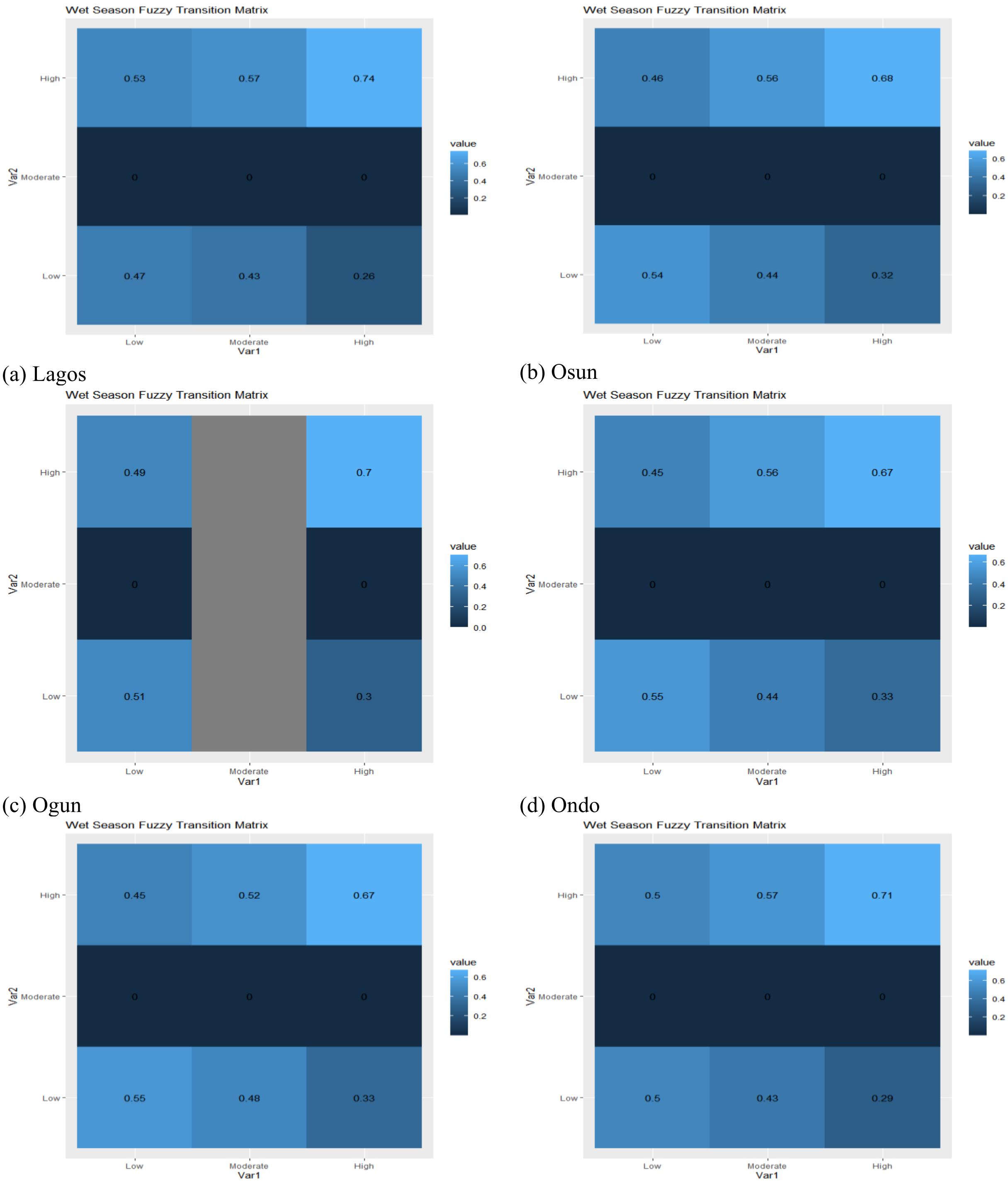


(e) Ekiti (f) Oyo

Figure 4: Wet Season Fuzzy Transition for Temperature across location

The Wet Season Fuzzy Transition Matrix for wind speed is presented in Figure 5. The results indicate that the high windspeed regime becomes more dominant during the wet season compared with the dry season. The highest membership values occur in the High to High state, with values of 0.75, 0.68, 0.70, 0.67, 0.67, and 0.71 for Lagos, Osun, Ogun, Ondo, Ekiti, and Oyo States, respectively. In fuzzy systems, high self-membership values indicate strong persistence and dominance of a particular state while simultaneously allowing overlap with other states (Zadeh, 1965; Zimmermann, 2010). The observed values therefore suggest that strong wind conditions remain the dominant atmospheric regime during the rainy season. This behaviour is consistent with the inherently continuous nature of atmospheric processes and the uncertainty associated with meteorological variables (Kosko, 1992). The increased dominance of high wind speeds during the wet season may be attributed to enhanced monsoon circulation, increased convective activity, mesoscale storm systems, and greater atmospheric instability associated with rainfall-producing weather systems (Nicholson, 2018). In coastal regions such as Lagos, sea-breeze circulations and interactions between maritime and continental air masses may further strengthen wind activity during the rainy season (Barry & Chorley, 2010). Consequently, the results suggest that wet season atmospheric conditions favour sustained periods of stronger winds across Southwestern Nigeria.

The membership values in the High row further indicate that high-wind conditions overlap substantially with both low and moderate wind regimes. This overlap implies that wet season wind variability is highly dynamic, with atmospheric conditions continuously fluctuating between relatively calm and intense wind states. Such behaviour is characteristic of tropical environments, where convective systems, thunderstorms, and monsoon disturbances generate rapid changes in wind speed and direction over short temporal scales (Ahrens & Henson, 2019). The overlap between wind regimes therefore reflects the gradual and continuous nature of atmospheric transitions rather than abrupt shifts between discrete states. A notable feature of Figure 5 is the complete absence of membership values in the Moderate row, where all entries are equal to zero. This suggests that the moderate windspeed regime does not possess a distinct or persistent atmospheric identity during the wet season. A state with negligible membership values contributes little to the characterization of the system and may represent a transitional rather than a dominant regime (Zimmermann, 2010). The absence of a stable moderate windspeed regime therefore highlights the highly dynamic nature of wet-season atmospheric circulation across Southwestern Nigeria and underscores the suitability of fuzzy approaches for representing overlapping climatic states and gradual transitions in wind-speed behaviour.



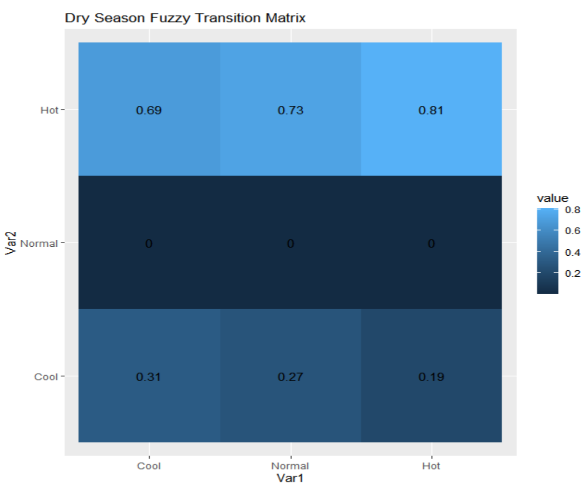
(a) Lagos (b) Osun (c) Ogun (d) Ondo (e) Ekiti (f) Oyo

Figure 5: Wet Season Fuzzy Transition for Wind speed across locations

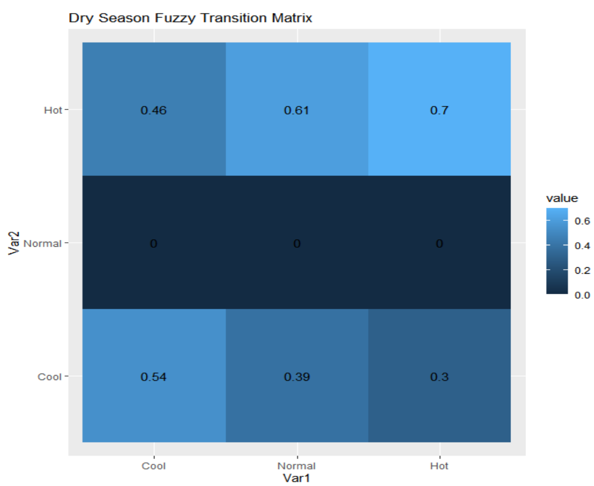
The Dry Season Fuzzy Transition Matrix (Figure 6) reveals a strong dominance of the hot temperature regime across Southwestern Nigeria. The highest membership values occur in the Hot to Hot state, with values of 0.81, 0.70, 0.72, 0.71, 0.70, and 0.71 for Lagos, Osun, Ogun, Ondo, Ekiti, and Oyo States, respectively. In fuzzy systems, high self-membership values indicate strong persistence and dominance of a particular state within the system (Zadeh, 1965; Zimmermann, 2010). These results therefore suggest that temperature conditions during the dry season are strongly associated with the hot regime and exhibit substantial persistence over time. Such dominance is characteristic of tropical dry season climates, which are typically associated with enhanced solar radiation, reduced cloud cover, limited rainfall activity, and increased sensible heat fluxes that promote atmospheric warming (Barry & Chorley, 2010; Nicholson, 2018).

The membership values linking the hot regime to other thermal regimes also demonstrate substantial overlap between hot conditions and neighbouring temperature states. This overlap indicates that although atmospheric conditions are predominantly hot, they still share partial characteristics with both normal and cool regimes. Such behaviour is a fundamental property of fuzzy systems, in which climatic states are represented as continuous and overlapping rather than discrete and mutually exclusive categories (Kosko, 1992; Zadeh, 1965).

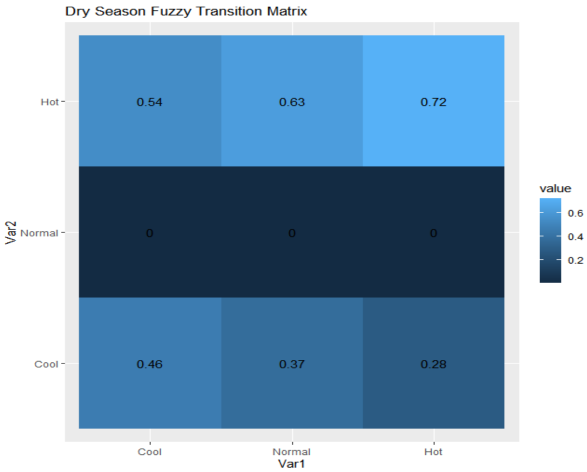
A particularly notable feature of Figures 4–6 is the complete absence of membership values in the Normal row, where all entries are equal to zero. The results suggest that the dry season atmosphere is largely polarized between cool and hot regimes. The absence of a stable normal regime implies that intermediate temperature conditions are either weakly expressed or short-lived. Similar behaviour has been observed in tropical climates, where seasonal contrasts often lead to the dominance of particular thermal regimes rather than prolonged persistence of transitional states (Nicholson, 2018). The comparatively lower membership values in the Cool row indicate weaker persistence and lower dominance of cool conditions relative to hot conditions. Nevertheless, the presence of non-zero memberships demonstrates that cool atmospheric characteristics still occur during the dry season, albeit with reduced frequency and intensity. Such conditions may arise from nocturnal radiative cooling, early-morning maritime influences, localized sea-breeze circulations, or temporary increases in cloud cover that reduce incoming solar radiation (Barry & Chorley, 2010). The fuzzy transition matrix demonstrates that the dry season thermal structure across Southwestern Nigeria is strongly skewed toward hot atmospheric conditions, characterized by persistent warming, weak persistence of cool states, and a near absence of stable normal temperature conditions. These findings highlight the suitability of fuzzy approaches for representing gradual climatic transitions and overlapping thermal regimes that cannot be adequately captured using conventional crisp-state classification methods (Kosko, 1992; Zadeh, 1965).



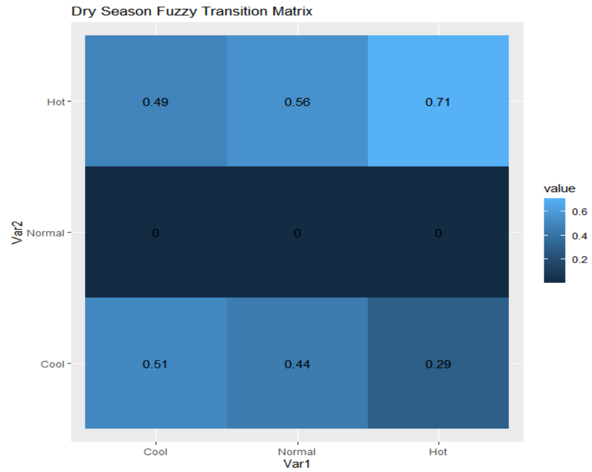
(a) Lagos



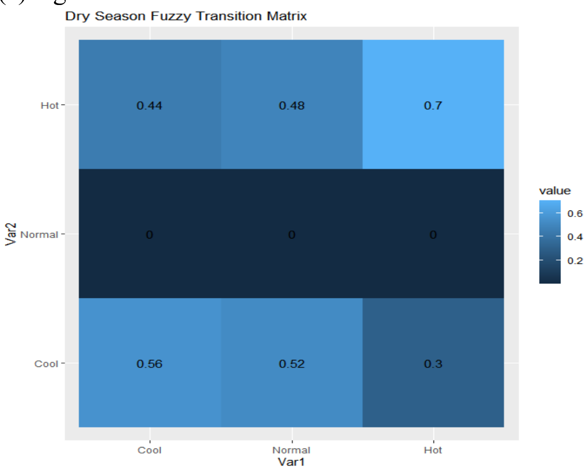
(b) Osun



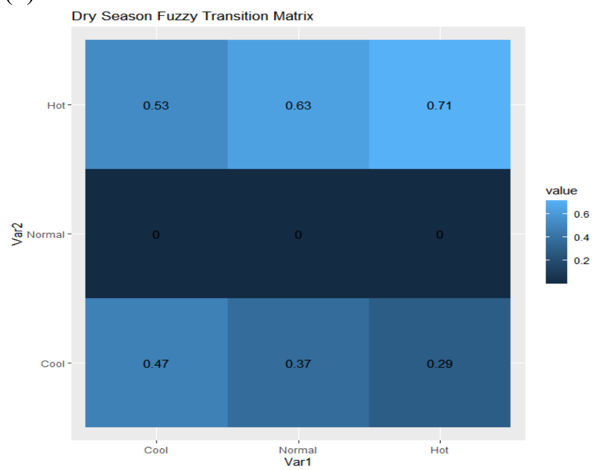
(c) Ogun



(d) Ondo



(e) Ekiti

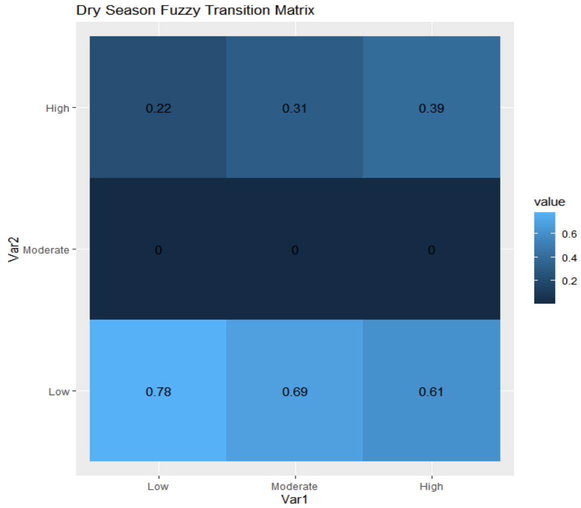


(f) Oyo

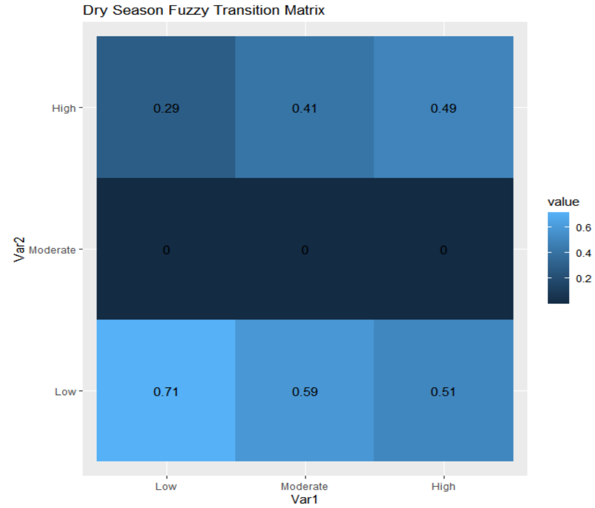
Figure 6: Dry Season Fuzzy Transition for Temperature across Locations

Figure 7 presents the Dry Season Fuzzy Transition Matrix for wind speed across Southwestern states in Nigeria. The results indicate that the low windspeed regime is the dominant atmospheric condition during the dry season. The highest membership values occur in the Low to Low state, with values of 0.78, 0.71, 0.74, 0.68, 0.72, and 0.75 for Lagos, Osun, Ogun, Ondo, Ekiti, and Oyo States, respectively. These findings therefore indicate that dry season wind conditions are strongly associated with the low wind regime and tend to remain stable over time. Such behaviour is consistent with the climatology of the West African dry season, during which reduced atmospheric moisture, weaker convective activity, and the dominance of relatively stable continental air masses often suppress sustained wind development (Nicholson, 2018). Consequently, the dry season atmospheric environment across Southwestern Nigeria appears to be largely characterized by calm or weak wind conditions.

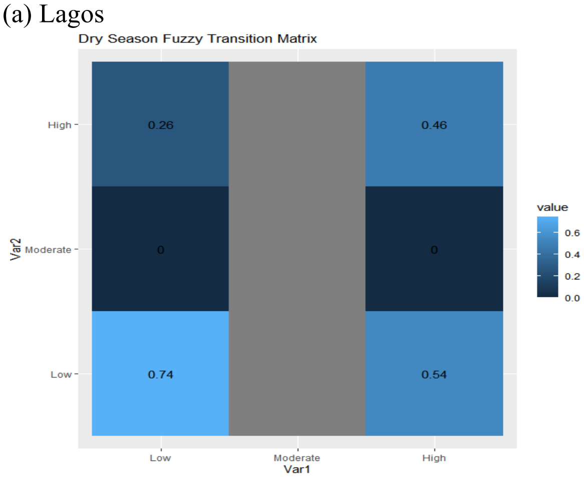
The membership values in the High row are comparatively lower, indicating weaker persistence and reduced dominance of strong wind conditions. Although high wind characteristics are present, they occur less frequently and exhibit lower stability than low wind conditions. This suggests that strong winds during the dry season are episodic rather than persistent atmospheric features. Such events may be associated with localized convective disturbances, transient pressure gradient adjustments, or occasional interactions between continental and maritime air masses (Ahrens & Henson, 2019). The relatively low persistence of the high wind regime therefore indicates that intense wind events do not constitute the dominant atmospheric state during the dry season. The absence of the moderate wind category in both the dry and wet season analyses for Ogun State is particularly noteworthy. This result suggests that the observed windspeed variability in Ogun exhibits a bimodal structure, characterized by oscillations between calm and relatively strong wind conditions with minimal persistence of intermediate wind speeds. Such bimodal behaviour implies that transitional wind states are either weakly expressed or short-lived. This pattern may be influenced by the state's proximity to the coast, interactions between land and sea-breeze circulations, rapid atmospheric adjustments associated with convective weather systems, and local land-surface heterogeneity (Barry & Chorley, 2010; Oke, 1982).



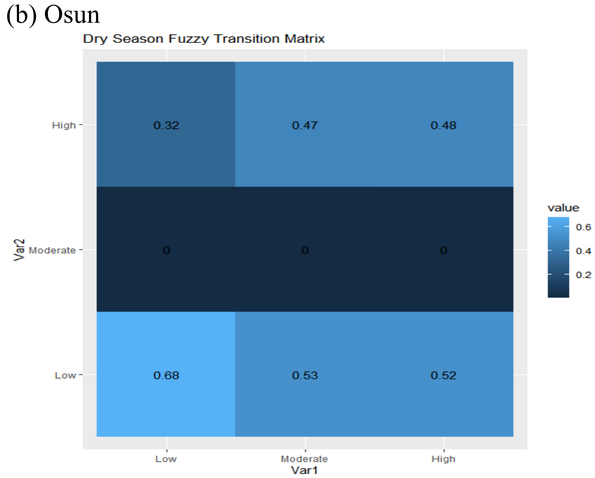
(a) Lagos



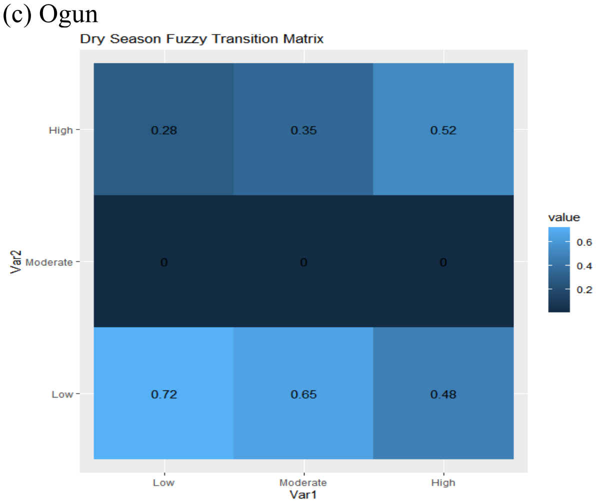
(b) Osun



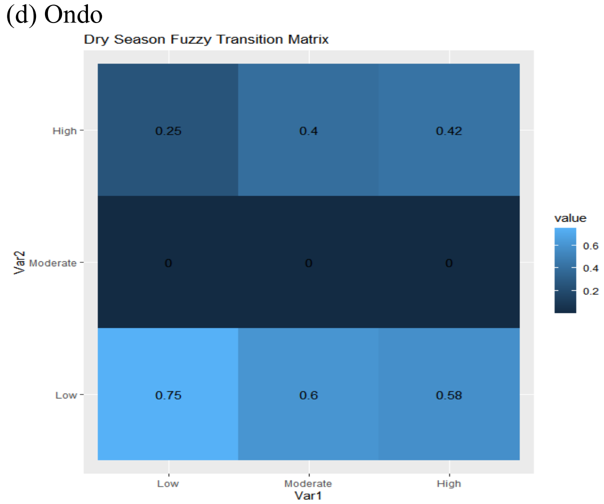
(c) Ogun



(d) Ondo



(e) Ekiti



(f) Oyo

Figure 7: Dry Season Fuzzy Transition for Temperature across Locations

The fuzzy transition analysis of temperature and wind speed in the Southwest of Nigeria reveals strong overlapping atmospheric behavior during the dry and wet seasons, indicating that climatic conditions do not exist as rigid or isolated states but instead possess varying degrees of belonging to multiple regimes simultaneously. The dry season is dominated by the hot regime, while the wet season shows stronger cool-state for temperature. Wind speed, on the other hand, exhibits dominant low wind conditions during the dry season and stronger high wind persistence during the wet season. The disappearance of the moderate regime is partly attributable to the percentile-based membership structure adopted in this study. Because the Moderate membership was computed as the residual term, observations were predominantly assigned higher memberships to the extreme states whenever values clustered near or beyond the percentile thresholds. Consequently, the intermediate regime accumulated very low transition weights and effectively disappeared from the normalized fuzzy transition matrices. Different threshold selections may produce alternative transition structures. The study is subject to certain limitation such as the fuzzy transition structure is sensitive to the percentile thresholds used for membership classification.

CONCLUSION

This study investigated the fuzzy transition dynamics of temperature and windspeed regimes in South-west, Nigeria using fuzzy Markov Model. The results demonstrated that atmospheric conditions in South-west exhibit strong overlapping characteristics and gradual transitions rather than rigid climatic boundaries. Temperature analysis revealed dominant hot conditions during the dry season and stronger cool-state persistence during the wet season, while windspeed analysis showed dominant low wind conditions in the dry season and stronger high wind persistence during the wet season. A major finding was the complete disappearance of stable moderate temperature and windspeed regimes, indicating weak intermediate atmospheric stability and dominance of climatic extremes across Southwestern Nigeria. The fuzzy membership framework successfully captured the degree of belonging of atmospheric conditions to multiple climatic states simultaneously, thereby providing a more realistic representation of tropical atmospheric variability compared to classical deterministic classification methods. The findings have practical implications for renewable energy planning, agricultural scheduling, climate adaptation strategies, and urban development policies. Understanding the persistence and transition behaviour of temperature and wind speed regimes can support climate resilient and decision making across Southwestern Nigeria. Future research should combine Fuzzy Markov Models with Artificial Neural Networks (ANN) to advance temperature and windspeed forecasting precision.

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