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Three-state Hidden Markov Model of Air Temperature Regimes over the Middle Belt States of Nigeria

*[1]Agada, Inikpi O., [2]Peter Onuche and [1]Audu, Moses O.

[1]Department of Physics, Joseph Sarwuan Tarka University, Makurdi. Benue State, Nigeria.
[2]Department of Statistics, Joseph Sarwuan Tarka University, Makurdi. Benue State, Nigeria.

*Corresponding author's email: agadainikpi020@gmail.com

ABSTRACT

This research applies a three-state Hidden Markov Model (HMM) to thirty (30) years (1991-2020) daily air temperature data over the Middle Belt states (Abuja, Benue, Kogi, Kwara, Nasarawa, Niger and Plateau) of Nigeria to identify the unique temperature regimes, characterize their distributional properties, and examine their temporal dynamics. Based on the state-dependent mean temperatures and standard deviation, the model divided the daily air temperature data series into three statistically different temperature regimes: regime 1 (Cool), regime 2 (Moderate), and regime 3 (Warm). Results show that the Warm (above average) regime dominates the majority of the time period, while the moderate (in-between) regime typically represents changes between transitional periods and the cool (below average) regime is associated primarily with the Harmattan (Northeast Trade Wind) Season. Transitions from Regime 1 (Cool) to Regime 2 (Moderate) and from Regime 2 to Regime 3 (Warm) happen more often than direct transitions from Regime 1 to Regime 3 as revealed by the Transition Probability Matrix. Warm regime occupancy reaches 54.4% in Benue and 45.7% in Kogi, indicating that high air temperature conditions dominate mainly in such area. The overall structure of the HMM used in this work provides a physical description of the temperature variability experienced by the Middle Belt States, Nigeria. Hence, creating a useful opportunities for assessments of climate variability, supporting heat-risk mapping and adaptation planning.

Keywords:
Hidden Markov Model,
Temperature Regimes,
Transition Probability,
State Occupancy,
Middle Belt states.

INTRODUCTION

Weather and climate variability are very critical to environmental processes, crop yields, water resources management as well as human comfort especially in tropical nations like Nigeria. Among the meteorological parameters, air temperature is an important and widely measured parameter, as it rapidly responds to variations in atmospheric conditions including cloud cover, solar radiation and rainfall. In Nigeria, past temperature-focused climate research typically have used trend analyses, time-series decomposition, and regression approaches to ascertain long-term temperature variance (Agada et al., 2023; Audu et al. 2022b; Agada et al., 2016; Amadi, 2014; Olofintoye and Sule, 2010; Ogolo and Adeyemi, 2009; Jain and Kumar, 2012; Oguntunde et al., 2012; Jones et al., 2013; Adefolalu, 2007; Ewona and Udo, 2008; Ragatao et. al., 2018; Adeniyi, 2020). All of these methodologies can be used to identify warming trends and seasonal variations; however, they do not include hidden weather states or allow for transitions between different types of climate regimes. An atmospheric condition or regime that is not directly measurable but affects the weather variables such as temperature, humidity, wind speed, pressure, or rainfall, is known as a hidden weather state (Zucchini and Guttorp, 1991).

Temperature behavior is frequently oversimplified by traditional statistical methods, which are unable to reflect stochastic transitions across weather regimes. However, atmospheric processes often display regime-dependent behavior and are intrinsically dynamic (Wilks, 2011). Large-scale circulation variations, moisture availability, and radiative forcing cause weather systems to fluctuate, resulting in temperature fluctuation that is dependent on the dominant atmospheric conditions, such as dry, overcast, or wet regimes (Ahrens, 2012). Since these weather regimes are not always readily observable, it is challenging to properly categorize and examine temperature trends using traditional linear techniques. Regime switching behavior in climate systems has been well studied, especially with regard to seasonal variations in atmospheric circulation and monsoon dynamics (Ghil et al., 2002). A framework for deriving unobservable atmospheric states from observed meteorological variables while taking probabilistic transitions across regimes into account is provided by hidden state models, specifically Hidden Markov Models (HMMs) (Rabiner, 1989; Zucchini, et al., 2016). Therefore, for better weather categorization and climate variability analysis, a modeling technique that can reflect the stochastic character of atmospheric transitions and infer hidden weather states from observable temperature data is required.

Stochastic models, like Hidden Markov Models (HMMs), provide a robust probabilistic framework for modeling such systems by linking observable input to unobservable (hidden) states. Depending on the current hidden weather state, temperature observations in an HMM are produced from probability distributions, and state transitions are governed by a Markov process. Diverse authors have applied the Hidden Markov Models (HMMs) in various fields such as: Bicego et al. (2003) in face recognition; Joshi et al., (2017) in weather prediction; Bhusari and Patil (2011) in credit card fraud detection; Zhang (2004) in prediction of financial time series; Xuan, (2004) in El Nino studies; Gales and Young, (2007) in speech pattern recognition; Tanguay, (1995) in gesture recognition and so on. HMM have been effectively used to describe seasonal rainfall dynamics, identify changes in the climate regime, and categorize wet and dry spells (Zucchini and Guttorp, 1991; Robertson, et al., 2004; Charles et al., 2004; Ailliot, et al., 2009; Laurence et al., 2009). The direct applications of HMMs specifically on air temperature regime classification over the Middle Belt States of Nigeria are rare. Hence, the aim of this study is to classify air temperature regime over the Middle Belt States (Abuja, Benue, Kogi, Kwara, Nasarawa, Niger and Plateau) of Nigeria using the three-state Hidden Markov Model (HMM), with a focus on understanding temperature variability and weather regime transitions within the climate.

MATERIALS AND METHODS

Study Area and Data

The Middle Belt States of Nigeria is a transitional zone that typically lies between latitudes 6°N and 11°30'N and longitudes 2°42'E and 15°E. It has a tropical wet (April-Oct) and dry (Nov-Mar) seasons that vary from South and North, with some places, like the Jos Plateau, having cooler temperatures. These states are known for its many ethnic groups and cultural diversity between the predominantly Hausa-Fulani North and the Yoruba/Igbo South. Nigeria's Middle Belt is a diverse central region that mainly includes the North Central geopolitical zone, which includes the Nasarawa, Plateau, Niger, Kogi, Kwara, Benue states, and the Federal Capital Territory (FCT). It also extends to southern portions of other northern states, such as Kaduna, Adamawa, Taraba, Bauchi, Kebbi, Gombe, and Yobe. Daily air temperature data for the core Middle Belt States in Nigeria from January1, 1991 to December 31, 2020 (30 years) was obtained from National Aeronautic and Space Administration (NASA) metrological center.

Figure 1: Map of Middle Belt States in Nigeria

Method

Hidden Markov Model (HMM)

Hidden Markov Models (HMMs) are a class of stochastic time-series models in which an unobserved (hidden) state process drives the generation of observed variables through state-dependent probability distributions. In meteorology and climate science, HMMs have been widely applied to identify and model distinct climate regimes based on observed data. The study employs a first-order Hidden Markov Model to classify daily mean temperature time series into latent weather states. The HMM consists of a discrete hidden state process that evolves according to a Markov chain, and a sequence of observed daily temperatures whose probability distributions are conditioned on the hidden states. An HMM is specified by the following components (Jurafsky and Martin, 2009):

$Q = q_1 q_2 \dots \dots \dots q_N$	A set of N states
$A = a_{11} \dots . a_{1j} \dots \dots \dots a_{NN}$	a transition probability matrix A, each a_{ij} representing the probability of moving from state i to state $j, s.t. \sum_{i=1}^{N} a_{ij} = 1\ \forall i$
$B = b_i(o_t)$	a sequence of observation likelihoods, also called emission probabilities, each expressing the probability of an observation o_t (drawn from a vocabulary $V = v_1, v_2, \dots \dots . ., vv_v$) being generated from a state q_i
$\pi = \pi_1 \pi_2 \dots \dots \dots \pi_N$	an initial probability distribution over states. π_i is the probability that the Markov chain will state in state i. Some states jay have $\pi_j = 0$, meaning that they cannot be initial states. Also, $\sum_{i=1}^{N} \pi_i = 1$

The HMM is given as input $= o_1 o_2 \dots o_N$: a sequence of T observations, each

One drawn from the vocabulary V. An HMM is said to be stationary if $\pi_0 = \pi_\infty$

A first-order Hidden Markov model instantiates two simplifying assumptions.

First, as with a first-order Markov chain, the probability of a particular state depends only on the previous state:

Markov Assumption: $P(q_i/q_1 \dots q_{i-1}) = P(q_i/q_{i-1})$ (1)

Secondly, the probability of an output observation o_i depends only on the state that produced the observation q_i and not on any other states or any other observations:

Output Independence:

$$P\left(o_i/q_1 \dots q_i q_{T,} o_1 \dots o_i . o_{T,}\right) = P(o_i/q_i) \qquad (2)$$

Duan et al., (2020) explicitly discuss that temperature distribution exhibit multiple regimes (not just two), which can be interpreted in terms of cool, baseline/normal, and warm/hot states. This justify the use of three states Hidden Markov Model and not two states HMM. In climatological applications, the three hidden states are Cool, Moderate and Warm temperature regime. Let $q_i \in \{1,2,3\}$ represent the three state HMM as shown below:

$$States = \begin{cases} Below\ average & 1{:}\ Cool\ Temperature\ regime \\ Average & 2{:}\ Moderate\ Temperature\ regime \\ Above\ Average & 3{:}\ Hot\ Temperature\ regime \end{cases} \qquad (3)$$

The hidden states satisfy a first-order Markov property (Eq. 1).

The transition probability P_{ij} between the three temperature regimes is governed by a 3x3 matrix (Agada et al., 2020):

$$P_{ij} = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} \qquad (4)$$

where $p_{ij} = P(q_i = j/q_{i-1} = i)$, each row sums to unity.

For air temperature data, it is commonly assumed to follow a Gaussian distribution:

$$Y_t/Q_t = k \sim \mathcal{N}(\mu_k, \sigma_k^2), \quad k = 1,2,3 \qquad (5)$$

Where:

$\mathcal{N}$ is the Gaussian probability density function

μ_k is the mean temperature of state k

σ_k^2 represents within − state temperature variability

The initial state distribution over hidden states is given as:

$$\pi = \{\pi_k\}, \quad \pi_k = P(q_1 = k) \quad \sum_{k=1}^{K} \pi_k = 1 \qquad (6)$$

This distribution reflects the likelihood of the climate system starting in each regime at the beginning of the observation period.

A three state temperature HMM is fully specified by:

$$\lambda = (\pi, P, \theta) \qquad (7)$$

Where

$\theta = \{(\mu_1, \sigma_1^2), (\mu_2, \sigma_2^2), (\mu_3, \sigma_3^2)\}$

The likelihood of the observation sequence is given as:

$$P(O/Q) = \prod_{i=1}^{T} P(o_i/q_i) \qquad (8)$$

The decoding task is the process of identifying which sequence of variables is the underlying source of a sequence of observations for any model, including HMM, that contains hidden variables. Rather, the Viterbi algorithm is the most widely used decoding algorithm for HMMs. In order to decode convolution codes over noisy digital communication links, Viterbi (1976) developed the Viterbi algorithm. Viterbi is a type of dynamic programming that uses a dynamic programming trellis, much like the forward algorithm. For a given state q_j at time t, the value $V_i(j)$ is computed as:

$$V_i(j) = \max_{i=1}^{N} V_{t-1}(i) a_{ij} b_j(o_t) \quad (9)$$

The three factors that are multiplied in Eq. (9) for extending the previous paths to compute the Viterbi probability $V_i(j)$ at time t are:

V_{t-1} the previous Viterbi path probability from the previous time step

a_{ij} the transition probability from previous state q_i to current state q_j

$b_j(o_t)$ The state observation likelihood of the observation symbol o_t given the current state j .

The Viterbi algorithm makes it possible to recognize dominant thermal regimes, analyze the persistence and duration of regimes, and finally detect gradual transitions between cool, moderate, and warm states. The Baum–Welch algorithm was used to calculate model parameters, such as Gaussian emission parameters and transition probabilities. In their investigation of statistical analysis of probabilistic functions of Markov chains, Baum et al. (1970) introduced the Baum–Welch algorithm (Joshi et al., 2017). This guarantees that the three thermal regimes are statistically represented as optimally as possible. The Hidden Markov Model estimation was performed using the depmixS4 R package.

RESULTS AND DISCUSSION

Time series plot of the daily air temperature recorded in Nigeria's middle belt states (Abuja, Benue, Kogi, Kwara, Nasarawa , Niger, and Plateau) over 30 years (1991-2020) is shown in Figure 1 (i–vii). The plots illustrates significant fluctuations in air temperature over study period. The Hidden Markov Model (HMM) classified the daily air temperature series for the Middle Belt states of Nigeria into three statistically distinct temperature regimes as State 1 (Cool), State 2 (Moderate), and State 3 (Warm) based on their state-dependent mean temperatures and related variability (Table 1). Table 2 displays the Transition Probability Matrix (TPM) for the Middle Belt States of Nigeria, and Figure 4(i-vii) displays the regime transitions graphically. The matrix captures the temporal dependence and persistence of temperature conditions throughout the Middle Belt states by summarizing the likelihood of changing from one temperature regime at day 's' to another regime at day 's+1'. In the HMM framework, such transition probabilities characterize regime persistence and switching dynamics (Zucchini et al., 2016).

Table 1: State Mean and Standard Deviation of Three State HMM Of Temperature Regime

Location	State	Mean Temperature	Stand. Dev.	Temperature Regime
	State 1	20.763	2.443	Cool
Abuja	State2	25.264	2.059	Moderate
	State 3	30.526	2.206	Warm
	State 1	21.032	2.872	Cool
Benue	State2	25.883	1.980	Moderate
	State 3	30.650	2.490	Warm
	State 1	21.764	2.624	Cool
Kogi	State2	26.227	1.839	Moderate
	State 3	30.896	1.756	Warm
	State 1	21.849	2.519	Cool
Kwara	State2	26.297	1.930	Moderate
	State 3	31.210	1.880	Warm
	State 1	21.577	2.077	Cool
Nasarawa	State2	25.828	2.175	Moderate
	State 3	31.238	1.738	Warm
	State 1	20.121	2.961	Cool
Niger	State2	25.315	2.233	Moderate
	State 3	29.819	2.659	Warm
	State 1	18.277	2.657	Cool
Plateau	State2	23.201	2.267	Moderate
	State 3	27.677	2.057	Warm

It is observed that the likelihood of staying in the Cool state is zero (0.000) across the study area. This implies that cool weather in the Middle Belt is erratic and temporary, most likely brought on by brief synoptic disruptions, heavy precipitation, or increased cloud cover. Also, annual temperature cycles are dominated by strong solar radiation and moderate seasonal temperature fluctuation, prolonged cool regimes are uncommon in tropical climates (Ahrens, 2012; Barry and Chorley, 2010). Rather, it shifts completely to the Moderate state (probability = 1.000 in Plateau, Abuja, Kogi, and Niger). The strong radiative forcing characteristic of tropical West Africa, where surface heating rapidly recovers moderate thermal conditions following brief cooling episodes, explains the abrupt transition from Cool to Moderate. Even if Moderate's diagonal entries are modest in some states, the structure suggests that Moderate serves as the Markov process's core or equilibrium regime. The West African monsoon system, which controls temperature fluctuation through cloud cover and moisture advection, may also be responsible for the moderate dominance (Nicholson, 2013). Especially during the dry season when cloud cover is lower and insolation is higher, these high diagonal probabilities suggest thermal stability once warm conditions are established. The lack or absence of direct Cool to Warm transitions indicates that warming happens gradually rather than suddenly throughout the Moderate regime.

According to tropical boundary layer thermodynamics, this sequential transition structure (Cool to Moderate to Warm) is consistent with slow atmospheric heating processes rather than abrupt regime jumps (Barry and Chorley, 2010). Given that the Jos Plateau has comparatively lower mean temperatures than the nearby lowlands, elevation effects may have an impact on the slightly more dispersed transition probabilities of the Plateau. In West Africa, where altitude dramatically alters thermal regimes, the impact of topography on temperature variability is well documented by Nicholson (2013). Temperature dynamics are better captured by stochastic state transition models than by single regime stationary time series models, as demonstrated by such regime-switching behavior (Hamilton, 1989; Zucchini et al., 2016). The important role of the moderate regime, shown by its relatively high transition probabilities presented in Table 2 and Figure 4(i-vii), confirms that the Middle Belt acts as a thermal transition zone between northern and southern Nigeria.

Table 2: Transition Probability Matrix

	States	Cool	Moderate	Warm
Abuja	Cool	0.000	1.000	0.000
	Moderate	0.973	0.026	0.001
	Warm	0.038	0.962	0.000
Benue	Cool	1.000	0.000	0.000
	Moderate	0.923	0.000	0.077
	Warm	0.000	0.981	0.019
Kogi	Cool	0.000	1.000	0.000
	Moderate	0.980	0.000	0.020
	Warm	0.000	0.956	0.044
Kwara	Cool	1.000	0.000	0.000
	Moderate	0.951	0.049	0.000
	Warm	0.030	0.951	0.019
Nasarawa	Cool	1.000	0.000	0.000
	Moderate	0.986	0.000	0.014
	Warm	0.000	0.971	0.029
Niger	Cool	0.000	1.000	0.000
	Moderate	0.959	0.041	0.000
	Warm	0.013	0.979	0.008
Plateau	Cool	0.000	1.000	0.000
	Moderate	0.935	0.037	0.028
	Warm	0.026	0.974	0.000

The State Occupancy of Cool, moderate, and warm hidden temperature regime in the core Middle Belt states is shown in Table 3. A Hidden Markov Model (HMM), which probabilistically divides observed temperature data into latent thermodynamic regimes, was used to infer these states (Rabiner, 1989; Zucchini et al., 2016). Each state's day distribution sheds light on the permanence, dominance, and regional climate structure of the regime. Abuja experiences 48.4% cool days, followed by warm (30.8%) and moderate (20.8%) days. Likewise, Nasarawa has 21.6% moderate, 29.3% Warm, and 49.1% Cool days. The large percentage of cool states indicates that the West African monsoon system's seasonal rainfall, cloud cover, and moisture advection all have a significant impact. Daytime temperatures are regulated when there is more cloud cover because less sunlight reaches the earth (Nicholson, 2013). In comparison to more southern states, Abuja may have somewhat lower temperatures due to its higher elevation in relation to the nearby lowlands (Barry and Chorley, 2010).

In Benue, only 11.7% of days are cool, compared to 54.4% of warm days. In a same vein, Kogi records 20.7% moderate, 33.6% Cool, and 45.7% Warm days. These states' (Beune and Kogi) lower elevation and greater exposure to northeastern dry-season continental air masses (Harmattan winds), which increase surface heating and decrease atmospheric moisture, are probably the main reasons why Warm regimes predominate there (Nicholson, 2013). This could also be attributed to River Benue and River Niger (in Kogi), the largest rivers in Nigeria which serve as heat reservoir (Audu and Isikwue, 2014; Audu et al., 2022a). Moderate days are the most common regime in Niger, accounting for 53.8% of all days. Likewise, 43.8% of Plateau's days are moderate. This points to rather constant temperatures devoid of protracted, intense heating or cooling. Altitude has a significant impact on the climatic behavior of the Plateau (Jos Plateau region), lowering mean temperatures through adiabatic cooling mechanisms (Barry and Chorley, 2010). The prevalence of moderate regimes suggests transitional seasonal features and thermodynamic stability. Kwara recorded 34.4% Warm, 25.0% Cool, and 40.6% Moderate. This balanced structure indicates that dry continental air masses and wet monsoon flow alternate yearly dominance, leading to frequent regime switching.

Figure 2 (i-vii) presents the distinct separation between the three state-dependent temperature regimes across Locations using HMM. As a result of the combined effects of solar heating and monsoonal moisture, the cool state has the lowest mean temperatures and less variability, the moderate state has intermediate thermal conditions, and the Warm state has the highest mean temperatures with more variability.

Table 3: State Occupancy (Number of Days and Percentage) Across Locations

Location	States	Number of Days	Percentage	Location	States	Number of Days	Percentage
Abuja	Cool	5303	48.4	Nasarawa	Cool	5383	49.1
	Moderate	2279	20.8		Moderate	2365	21.6
	Warm	3376	30.8		Warm	3210	29.3
Benue	Cool	1279	11.7	Niger	Cool	1912	16.9
	Moderate	3716	33.9		Moderate	6089	53.8
	Warm	5963	54.4		Warm	3322	29.3
Kogi	Cool	3680	33.6	Plateau	Cool	3356	30.6
	Moderate	2265	20.7		Moderate	4799	43.8
	Warm	5013	45.7		Warm	2803	25.6
Kwara	Cool	2742	25.0				
	Moderate	4448	40.6				
	Warm	3768	34.4				

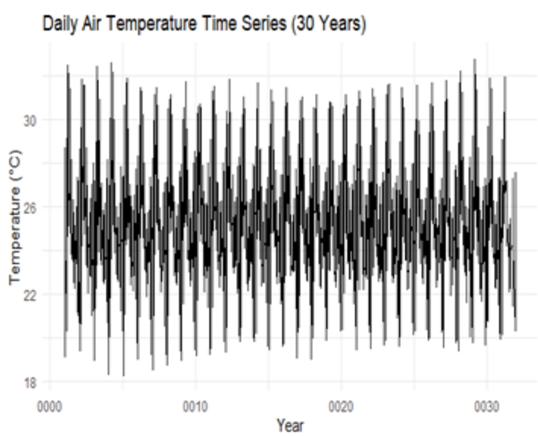
While State 3 (Warm) shows a wider distribution consistent with increased convective activity and thermal variability during the wet season, State 1 (Cool) shows a narrow distribution suggestive of stable Harmattan-related conditions. The partial overlap of State 2 (Moderate) with both extremes highlights its transitional role in the Middle Belt climate. Different physical mechanisms such as increased solar insolation and moisture-induced heat retention drive warmer conditions, while dry continental air masses and radiative cooling sustain cooler conditions plays a major role over the Middle Belt climate. Periods when these conflicting factors coexist and produce intermediate thermal conditions are captured by the moderate state. Additionally, topography affects the distribution of cool and moderate states, especially in regions like the Jos Plateau where lower temperatures may last longer (Barry and Chorley, 2010). The HMM successfully differentiates between various thermal states, as shown by the state-dependent temperature distributions by HMM (Figure 3 (i-vii)), which clearly show separation between the three regimes.

The monthly distributions of the three hidden temperature regimes (Warm, Moderate, and Cool) for the core Middle Belt states in Nigeria are shown in Figure 5(i–vii). The findings show that the occurrence of the regime exhibits distinct seasonal structuring. According to Nicholson, (2013), the wet season's increased cloudiness lowers daytime temperatures by reducing incoming solar radiation. Abuja and Nasarawa experience the cool temperature regime more frequently, indicating a greater impact from the West African monsoon system's seasonal cloud cover, rainfall, and moisture advection. In Kwara, Niger, and the Plateau, the moderate temperature regime occurs with an intermediate frequency. According to Barry and Chorley (2010), the elevated terrain of Plateau State, namely the Jos Plateau, is known to lower mean air temperatures through adiabatic cooling mechanisms, encouraging thermally stable or moderate conditions in comparison to the nearby lowlands. The transitional atmospheric conditions between peak dry-season warmth and monsoon-driven cooling are probably represented by the moderate regime.

On the other hand, Benue and Kogi are where the Warm temperature regime is most common, suggesting extended periods of intense surface warmth. These states are located in the tropical savanna climate zone, which is distinguished by high insolation and noticeable dry seasons (Peel, et al., 2007).Warm regime dominance is more likely during the dry season due to enhanced solar heating caused by reduced cloud cover and the effect of continental tropical air masses has stated by Nicholson, (2013). The Warm regime's predominance throughout the yearly cycle demonstrates that the Middle Belt has more months with intense surface heating than months with Harmattan induced cooling. Between December and February, northern Nigeria is usually hit by the Harmattan, a dry and dusty northeasterly wind from the Sahara that brings with it comparatively colder mornings and lower humidity, albeit for a shorter period of time than the longer warm season (Barry and Chorley, 2010). The tropical thermal structure of central Nigeria, where high solar input predominates for a large portion of the year, is reflected in this hierarchy.

CONCLUSION

The three states Hidden Markov Model (HMM) identified three temperature regimes with clear physical definitions: Cool, Moderate, and Warm, which have different climatic characteristics and statistics. The results of state-dependent temperature distributions and state-occupancy rates have given us more understanding about the causes of the variability in temperature than prior mean-dependent analyses had given us. Transition probability matrix reveals that straight transitions from regime 1 (cool) to regime 3 (warm) are uncommon. Changes in transition probabilities or regime frequency may be used as early warning signs of long-term change and climate variability. The HMM provides a significant interpretation of the thermal energy system of the Middle Belt States of Nigeria in addition to quantifying statistical temperature regime dynamics. Future studies should create a coupled thermodynamic hydrological regime model by including other climate factors such as humidity, wind speed, or rainfall. In West Africa, such additions might improve the forecasting ability of stochastic climate models and deepen our understanding of tropical temperature dynamics.



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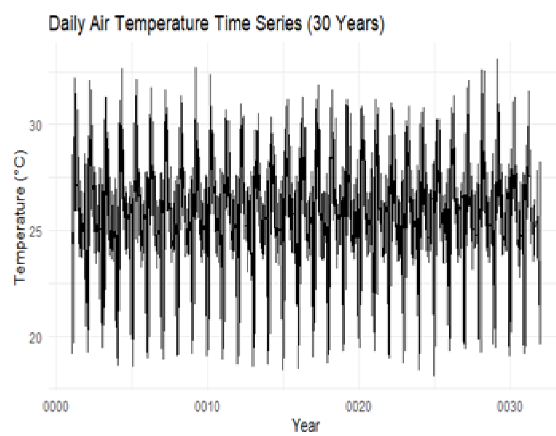
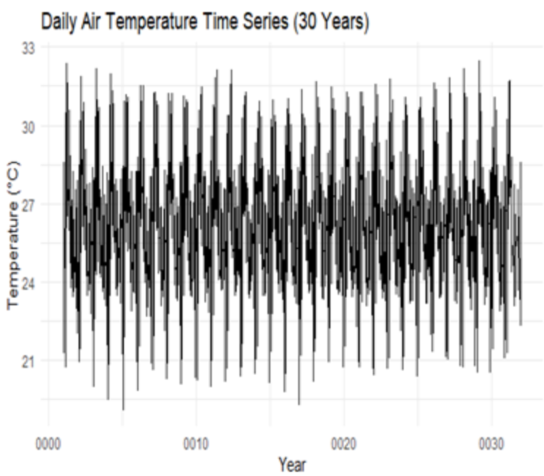
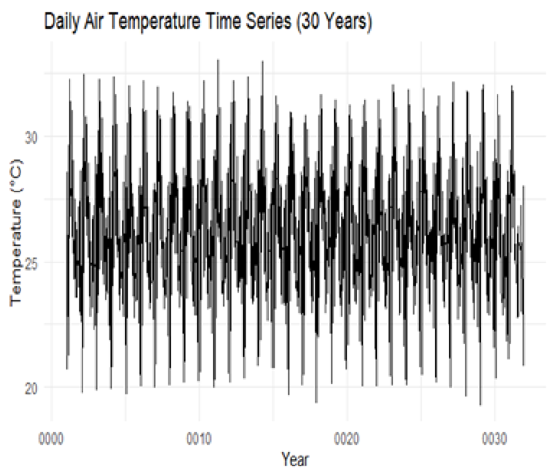


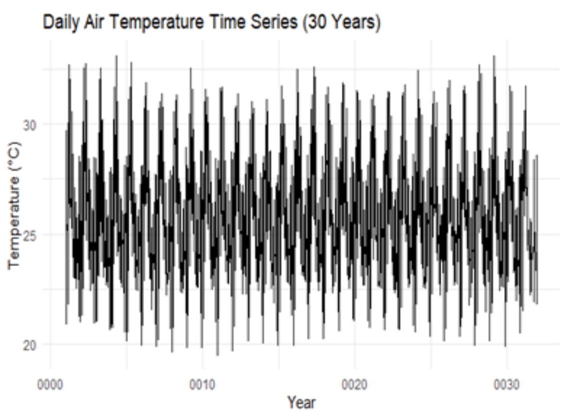
(ii) Benue



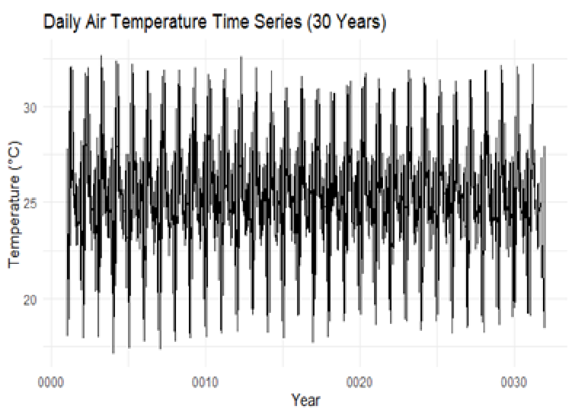
(iii) Kogi



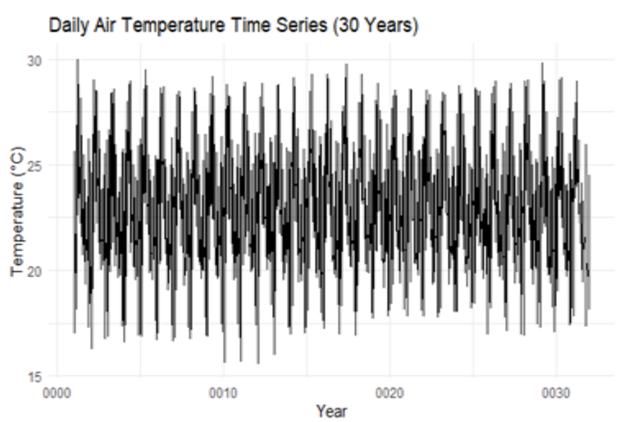
(iv) Kwara



(v) Nasarawa

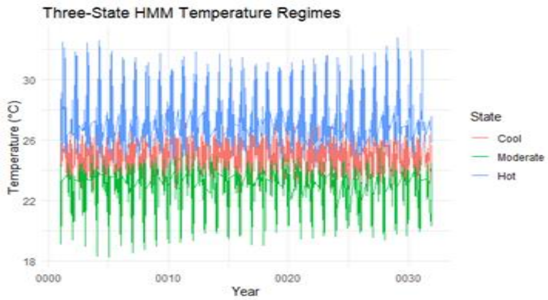


(vi) Niger



(vii) Plateau

Appendix 1: Daily Air Temperature Time Series across Locations



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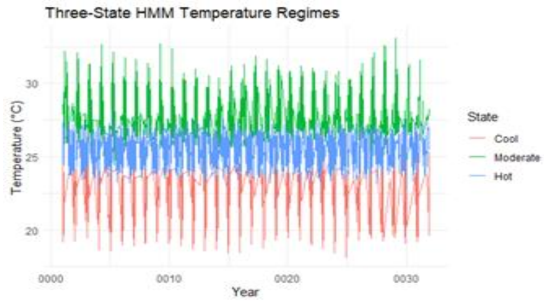
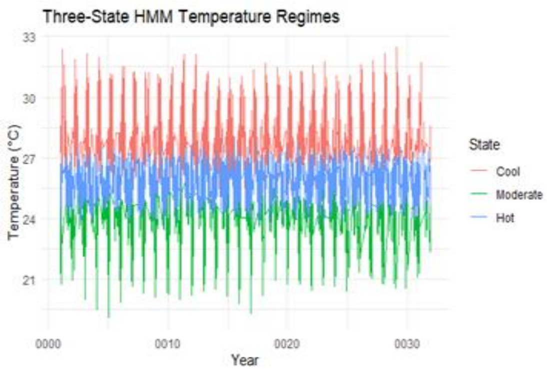
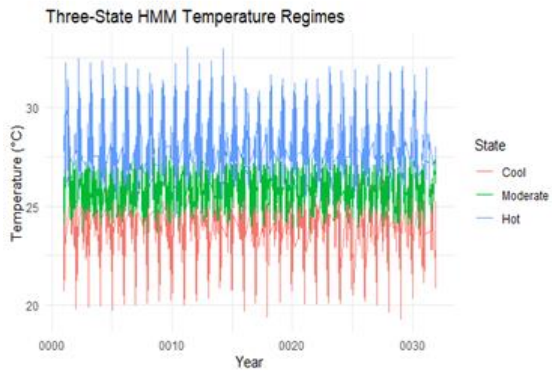


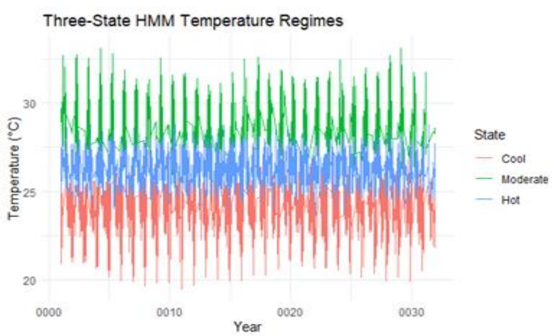
(ii) Benue



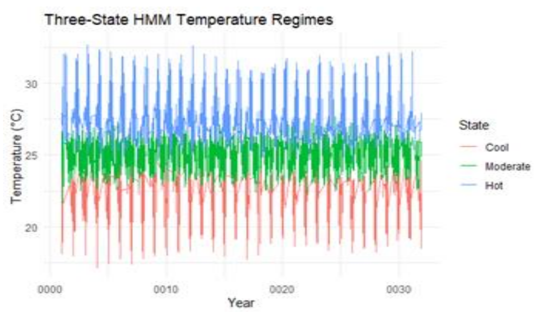
(iii) Kogi



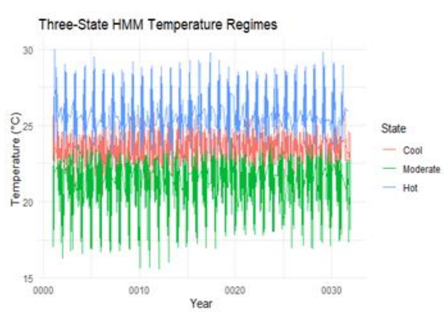
(iv) Kwara



(v) Nasarawa

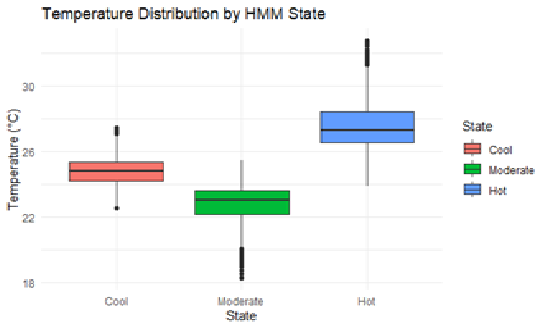


(vi) Niger

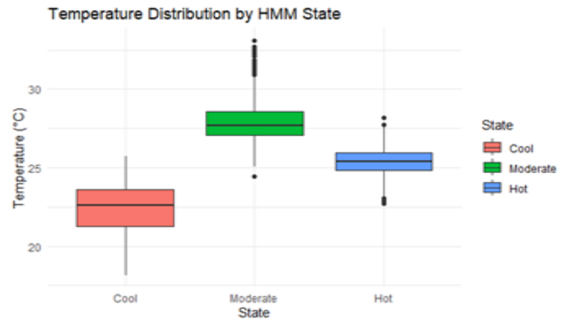


(vii) Plateau

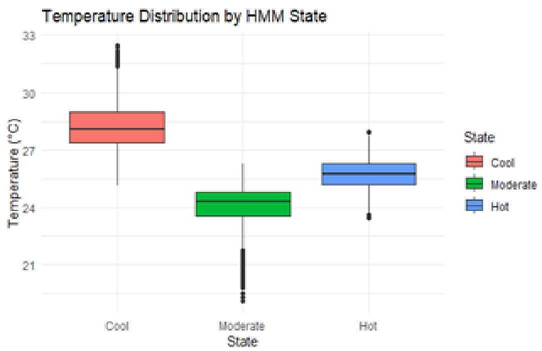
Appendix 2: Three- State dependent HMM Temperature Regimes across Locations



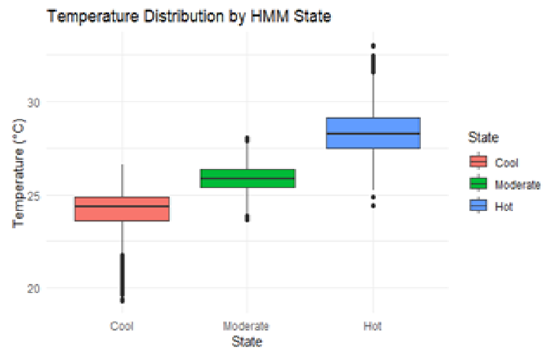
(i) Abuja



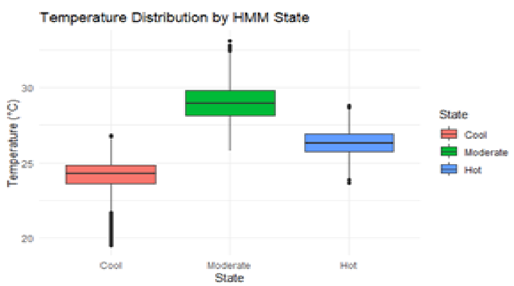
(ii) Benue



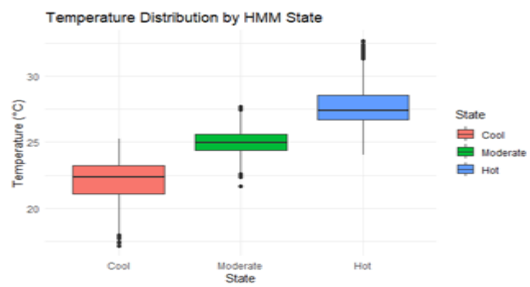
(iii) Kogi



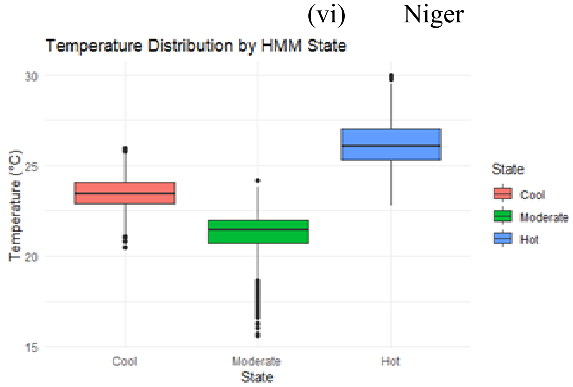
(iv) Kwara



(v) Nasarawa

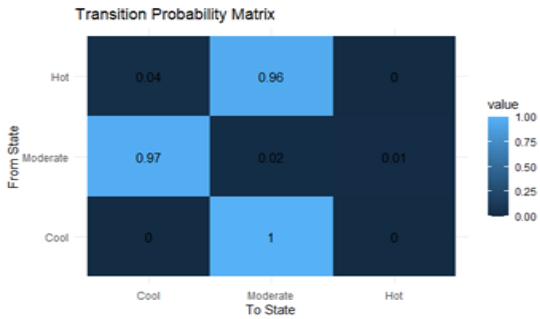


(vi) Niger

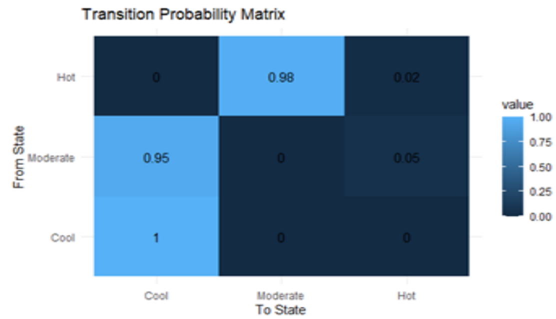


(vii) Plateau

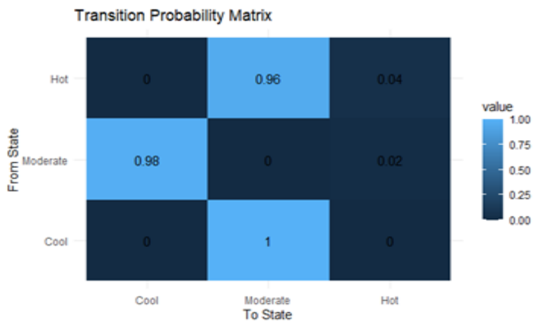
Appendix 3: Temperature Distribution by HMM State across Locations



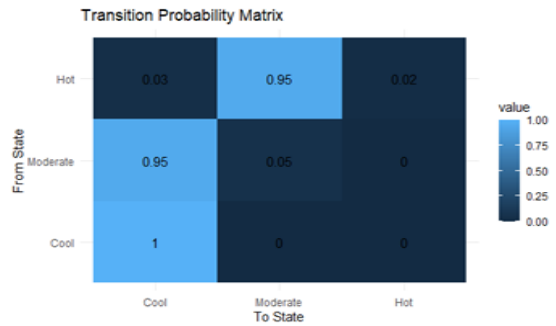
(i) Abuja



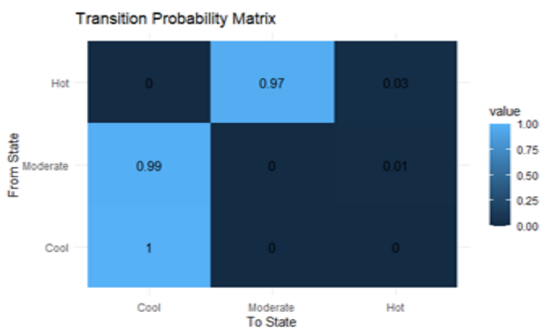
(ii) Benue



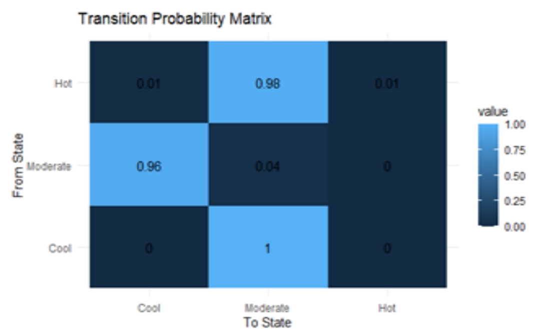
(iii) Kogi



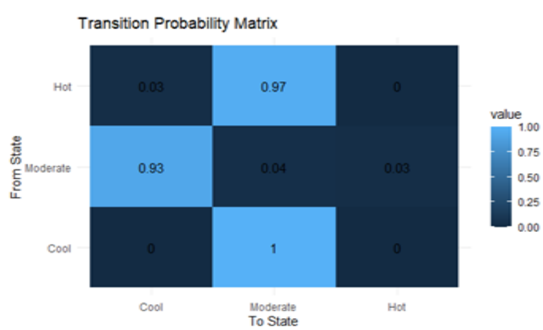
(iv) Kwara



(v) Nasarawa

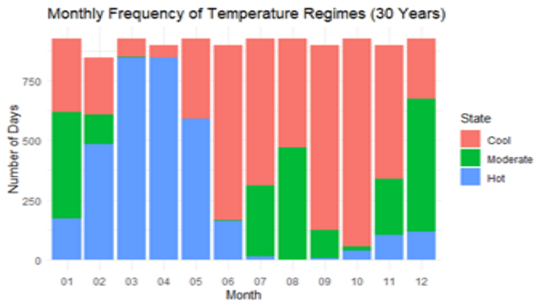


(vi) Niger

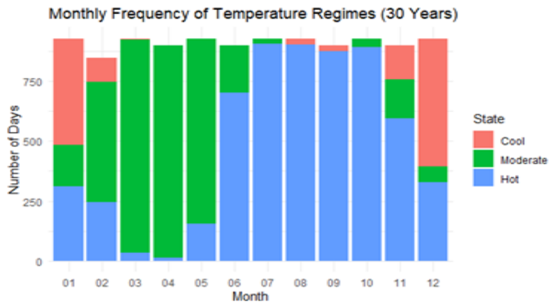


(vii) Plateau

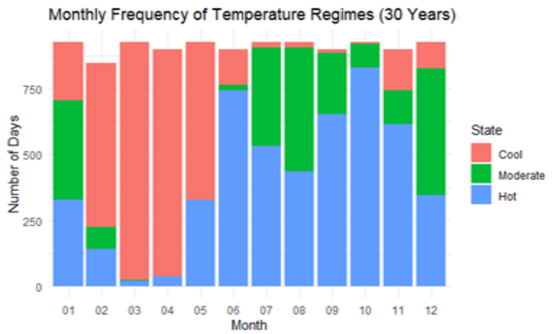
Appendix 4: Transition Probability Matrix across Locations



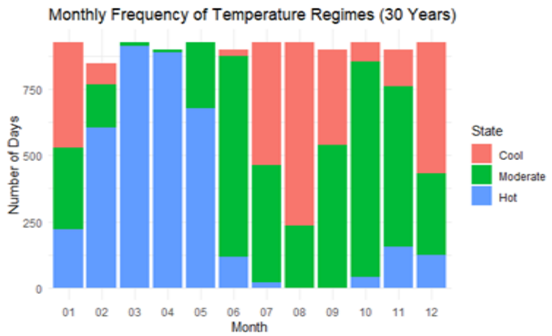
(i) Abuja



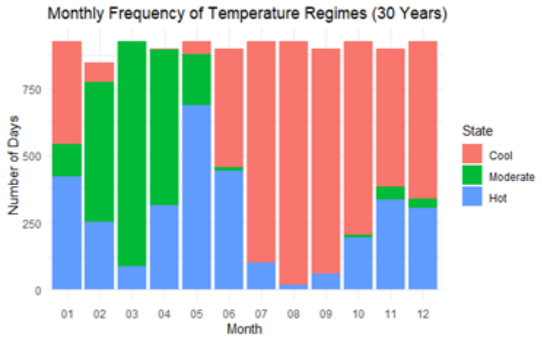
(ii) Benue



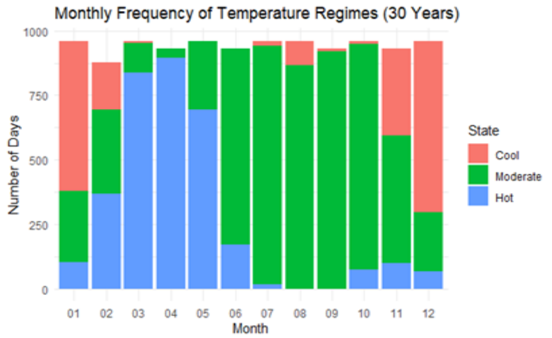
(iii) Kogi



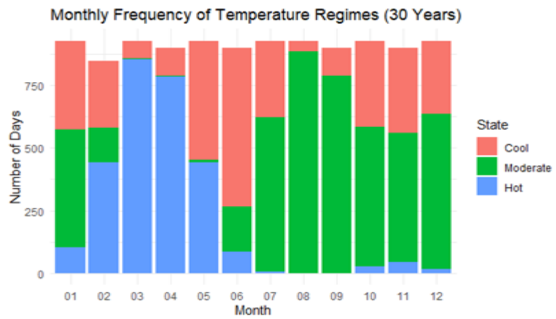
(iv) Kwara



(v) Nasarawa



(vi) Niger



(vii) Plateau

Appendix 5: Monthly Frequency of Temperature Regimes across Location

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