MODIFICATION OF THE THERMAL COMFORT INDEX BASED ON PERCEPTIONS FOR URBAN TOURISM AROUND JAKARTA

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ABSTRACT

Climate interaction directly correlates with an individual's comfort response. One's comfort can be quantified by perceiving environmental conditions at tourist locations. This study aims to identify climatic and non-climatic factors that affect thermal comfort based on visitor perception. In addition, the Holiday Climate Index (HCI) is modified to equalize visitors' perceptions. The research locations, namely Taman Mini Indonesia Indah (TMII), Kebun Raya Bogor (KRB), and Taman Safari Indonesia (TSI), are characterized by distinct topographies. This study identifies thermal comfort factors based on 552 questionnaire responses from purposive sampling. Analyzing factors influencing thermal comfort using ordinal logistic regression with Uncomfortable Class (0) and Comfortable Class (1). Model performance metrics, such as accuracy, precision, recall, and F1 score, are calculated using a confusion matrix. In general, the best time to feel comfortable is in the morning. Overall, climatic factors such as thermal sensation and rainfall events influence thermal comfort, while non-climatic factors have no effect. The model's implication is to provide an equation in the probability of someone feeling comfortable or uncomfortable based on the predictors. Furthermore, a modification index at TMII adjusted the HCI-urban's weighting, ratings, and comfort thresholds to match visitors' perceptions at that time. The results demonstrate that HCI-urban effectively provides comfortable and comfortable assessments. However, it has not yet been able to capture perceptions of discomfort, unlike the modified index. This research can provide added value to the tourism industry in terms of maintaining environmental comfort during the dry season.

Keywords: urban tourism, climate indices, thermal comfort, modification index, tropical landscape

1. Introduction

Tourism is closely related to the business sector [1] and the diversification of tourist destinations [2]. Moreover, tourism can potentially drive a country's economic engine [3]. The economic impact resulting from tourist visits manifests in the increased development of comprehensive facilities and infrastructure [4]. Discussing tourism inevitably leads to considerations of the destinations people visit. Indonesia boasts a diverse range of tourism types, including cultural, local wisdom, natural attractions and tourist villages. The nexus between tourism and weather parameters is inseparable, as both are decisive factors in the decision-making process for travel. Information regarding weather and climate, such as thermal comfort, is crucial for selecting tourist destinations that travellers intend to visit [5]. Choosing a tourist location may involve weather predictions to minimize errors in determining the timing of visits. Incorrect vacation timing can affect the biological comfort of travellers [6], indicating that climate parameters influence activities during tourism. Temperature, humidity, and rainfall can cause discomfort and have negative health effects [7]. Furthermore, another climate factor influencing tourists' decisions to visit is the duration of seasons [8]. In addition to climate factors, comfort perceptions are also influenced by the duration [9] and the design of airflow [10]. The comfort assessment depends on individual preferences for activities at a tourist location. Common activities during tourism include walking, jogging, and sitting, each with varying levels of metabolic activity. The higher the activity level, the greater the energy expended [11].

The climate and non-climate parameters are inherently intertwined in shaping the perception of comfort during tourism. Comfort responses emerge from the interaction of weather and climate. Climate change poses a particular challenge, especially in the tourism sector, negatively impacting various climate parameters such as precipitation, radiation, and wind. When these parameters experience an increase, they contribute to altering the climate comfort in a location [12]. Similarly, a 1% increase in climate parameters such as air temperature and relative humidity concerning to the average value also results in a 1.37% decrease in foreign tourist visits to Indonesia [13].

Information derived from climate parameters is crucial for tourists, both in terms of timing and location. The presentation of such information aims to provide an overview of comfortable and uncomfortable places and periods based on numerical calculations of thermal comfort indices derived from climate data. Differences in thermal comfort perceptions at a particular location vary depending on climatic and non-climatic factors. These perceptions were assessed through surveys targeting both tourists and students. Comfort preferences depend on seasonal conditions, wind speed, and age [14]. Thermal comfort perceptions in outdoor spaces are also influenced by environmental temperature [15]. Elevated environmental temperatures, often attributed to physical development (urban morphology), can induce uncomfortable thermal sensations [16].

Several indices representing comfort have been extensively studied, such as the Universal Thermal Comfort Index (UTCI), Physiologically Equivalent Temperature (PET), and Temperature Humidity Index (THI) which consider indoor comfort [17], which consider indoor comfort. UTCI depicts human bioclimatic conditions outdoors [18] However, UTCI has limitations, as it assumes a constant metabolic rate and considers clothing types uniform with environmental temperatures [19]. PET is one index used in the context of urban design and human behaviour [20]. Practically, PET has yet to be applied in high humidity conditions without estimating humidity factors [21]. Another index relevant to the tourism sector is the Tourism Climate Index (TCI) introduced by Meickowski [22], with the most popular being the Holiday Climate Index (HCI) based on daily average data [23]. TCI has been studied for decades to determine the best times for tourism. In Indonesia, TCI has been analyzed concerning tourism visits to the Borobudur Temple area [24] and the best times for beach tourism [25] However, TCI data formatting uses monthly scales, while visitors often vacation on weekly or even daily scales.

Unlike TCI, HCI is an index based on daily data, making it easier to calculate current and future comfort values [23]. HCI application is divided into two tourist locations: beach tourism (HCI-beach) and urban tourism (HCI-urban). HCI-urban use extends beyond city tourism to rural areas [26]. HCI can also be used to analyze the spatial distribution of comfort shifts in the future [27] and is closely related to tourist visits [28]. Each index has its strengths and weaknesses regarding subjectivity [29] and validation [30].

HCI was developed in subtropical regions by adapting existing perceptions in those areas. Other studies on HCI often only calculate spatial and temporal distribution rather than evaluating the index at specific locations. However, HCI evaluation in tropical regions has yet to be comprehensively studied, especially concerning comparisons between HCI values and visitor perceptions. The first goal of the study is to identify climatic and non-climatic parameters influencing thermal comfort based on tourist perceptions at three tourist sites. The second goal is to present a modified thermal comfort index based on climate data for 15 years. This modified thermal index is then compared with the existing index and visitor perception.

2. Methods

This research was conducted in locations with varying elevations: Taman Mini Indonesia Indah (TMII), Kebun Raya Bogor (KRB), and Taman Safari Indonesia (TSI). TMII is one of the tourist destinations that embraces a modern-classic theme. The tourism concept offered at TMII leans more towards semi-outdoor activities, cultural landscapes, and education. TMII is situated at a low elevation, 41 meters above sea level. In 2022, TMII was the second leading tourist destination in DKI Jakarta, with a visitation count of 1,057,316 people [30]. Nature-based tourism design is predominant in KRB and TSI. KRB is topographically higher than TMII and is located in the Central Bogor District of Bogor City. The elevation difference between KRB and TMII is approximately 221 meters above sea level. Meanwhile, TSI's elevation reaches 1,190 meters above sea level, making it a preferred tourist destination, especially for the Jakarta surrounding area. Details of the research location are shown in Figure 1.

The research was conducted from June 1 to August 31, 2023. The data was divided into primary data (questionnaires) and secondary data (climate data). Preliminary data consists of perception data obtained through purposive sampling from tourists. Primary data collection was conducted twice daily, in the morning (09:00 – 10:00) and afternoon (12:00 – 13:00). This writing will emphasize comfort perceptions based on the sensations of temperature, wind, clouds and rainfall events. Each parameter's perception has different levels. The total number of respondents during the three months was 552 local tourists. Each location consists of 184 respondents, with a distribution of 92 respondents each for morning and afternoon. The sampling criteria included a minimum age of 17, a high school education, and being a tourist.

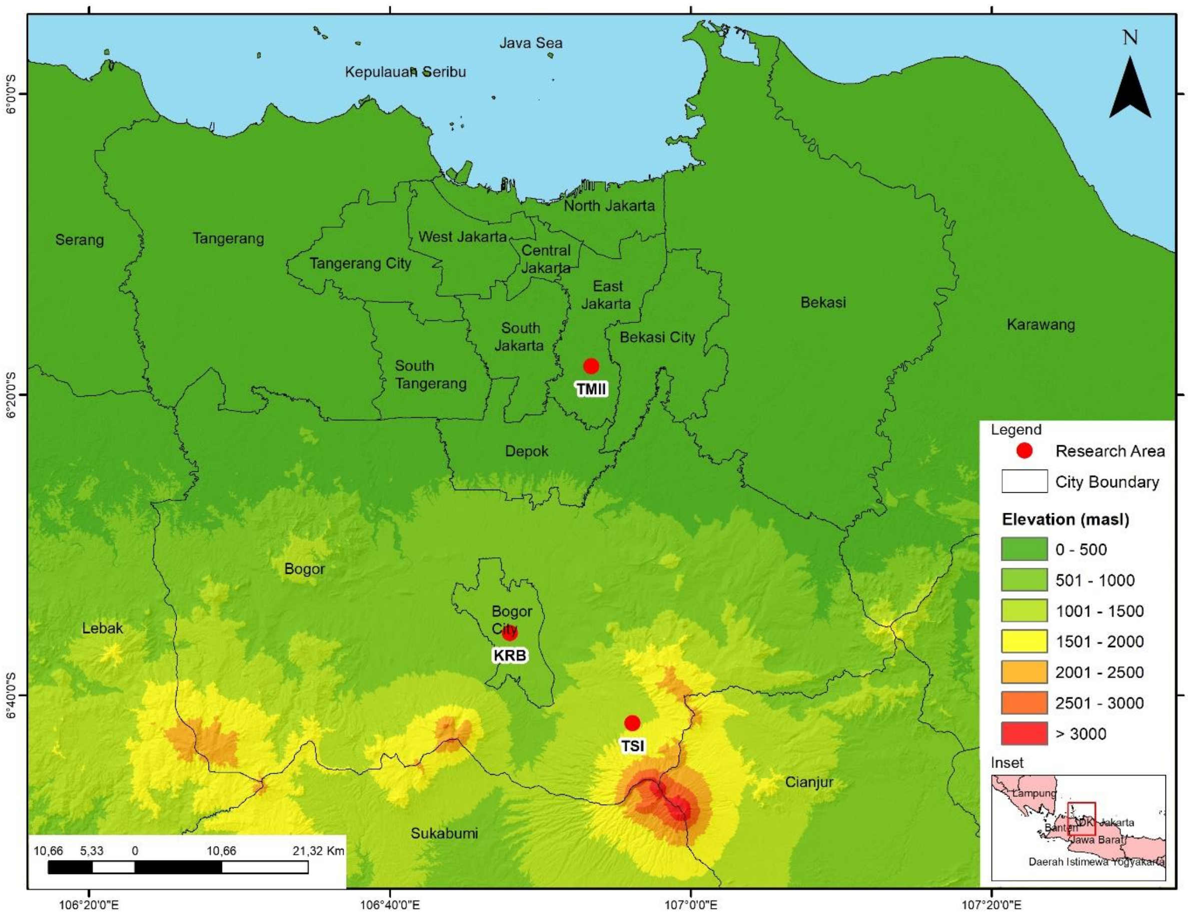


Figure 1. **Research location**

Secondary data is divided into daily average climate data for 2008 – 2022 and used as the basis for index development and verification data. The first dataset is employed to understand profiles in a time series and data distribution. The second set, verification data, will be analyzed in histograms to facilitate the creation of classes for each sub-index. Data sources are from the Indonesia Agency for Meteorology, Climatology, and Geophysics (BMKG). Verification data is collected hourly from the Automatic Weather Station (AWS) BMKG. The AWS device's location is within the TMII area (East Jakarta).

Meanwhile, the daily average time series climate data spanning 15 years is sourced from the Halim Perdana Kusuma Meteorological Station. The representation of TMII data is derived from weather observation stations close to the research site. The research site's varying elevations are illustrated in Figure 1. It is evident from the Data Elevation Model (DEM) that the TSI location is higher compared to the other two places. AWS data used include maximum temperature (Tmax), average temperature (Tavg), minimum temperature (Tmin), relative humidity (RH), total precipitation (RR), and wind speed (WS). Additionally, manually observed data includes cloud cover, as AWS does not monitor this parameter. The data period is from June 1 to August 31, 2023, every hour from 09:00 to 15:00 on a daily average basis. Rainfall data is processed by summing the amount of rain during that time range, chosen based on the optimal time for tourism activities.

The initial stage of this research was collecting primary data in the form of respondent data at three tourist locations. The preliminary data aims to determine the perception of comfort felt by visitors on that day. The perception data is then grouped into several criteria, as in Tables 1 and 2. The next step is to process the data using the ordinal logistic regression equation. This analysis aims to identify the climate and non-climate variables that influence thermal comfort. The second stage is processing secondary data (climate data) to determine the comfort value at TMII based on the HCI method. The third stage is modifying the ratings and weights of the climate data and respondents. The technique for modifying the thermal comfort index is to create a histogram using the Sturges Rule method [30] for each climate parameter, namely normal effective temperature (NET), wind speed, cloud cover and rainfall. The outline of this research can be shown in the flowchart diagram in Figure 2.

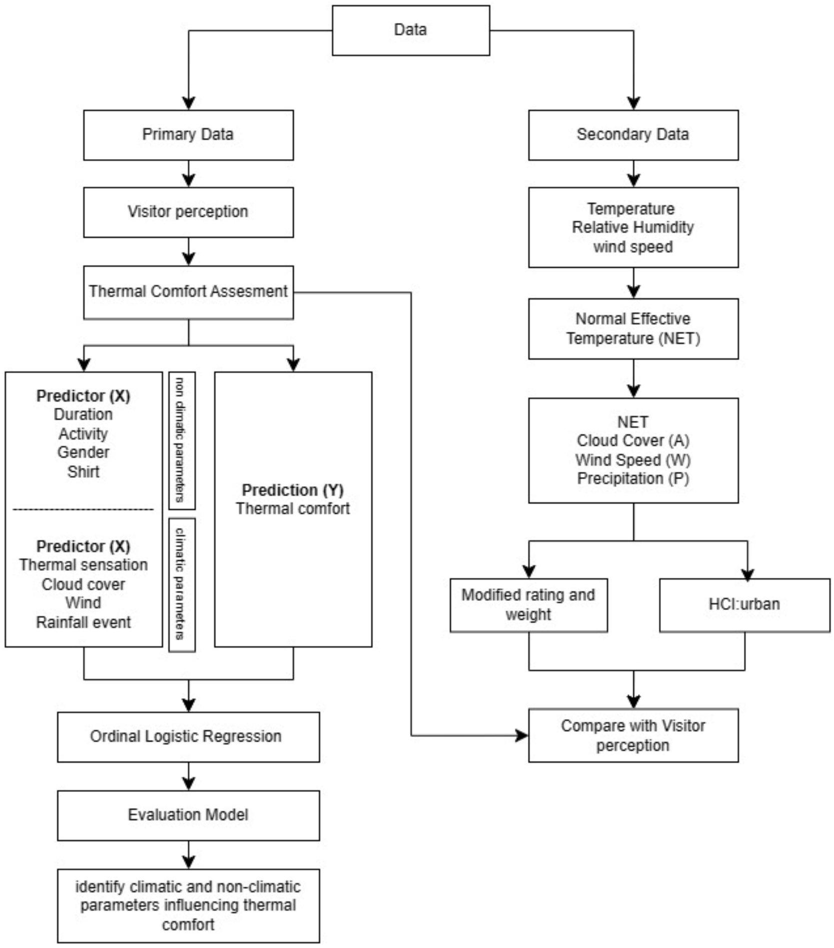


Figure 2. Flowchart research

Statistics Analysis. The questionnaire data were inputted using a Microsoft Excel to facilitate subsequent calculation processes. Data processing, such as logistic regression, was done using Python programming. This research utilizes a statistical method, ordinal logistic regression, to analyze the response variable with an ordinal scale [31]. Predictor variables in the logistic regression model are categorical. The probability of thermal comfort can be calculated using ordinal logistic regression. The dependent variable (Y) represents the level of comfort for each individual, categorized as uncomfortable (0) and comfort (1). Factors influencing thermal comfort are categorized into: climate and non-climate factors. Table 1 outlines the details of non-climate variables as predictors (X) related to the current perceived weather conditions. Non-climate variables consist of duration, type of activity, gender, clothing worn and frequent visits showed in Table 2. Each category has a different numerical scale.

Visit duration is divided into less than five and more than five hours. A visitor duration of less than five hours is synonymous with short activities such as jogging. The type of activity carried out during the trip is also recorded, whether light (leisurely walking) or moderate. Other things such as gender (male or female), color of clothes worn (dark or light) and frequency of visits (less than five times or more than five times) were also asked of respondents.

The weather conditions experienced during the interview were also recorded according to the visitor's perception. Thermal and wind sensations have the same five levels. Thermal sensation has five levels ranging from very cold to hot. The wind sensation also has five levels: no wind to strong wind. Meanwhile, cloud cover has two categories: clouds and clear skies. Lastly, visitors are also observed and asked about whether there is rain or not. If visitors don't know that it has rained, the officers will fill in according to the weather in the field.

Table 1. Perception of non climate sensation

Non climatic variable				
Duration	**Activity**	**Gender**	**Shirt**	**Frequent visits**
Less than 5 hour (0)	light (0)	Male (0)	Dark (0)	Less than 5 times (0)
More than 5 hour (1)	Medium (1)	Female (1)	Bright (1)	More than 5 times (1)

Table 2. Perception of climate sensation

Climatic variable			
Temperature	**Wind**	**Cloud Cover**	**Rainfall event**
Very cold (1)	No wind (1)	Cloudy (0)	No rain (0)
Cold (2)	Little wind (2)	Sunny (1)	Rain (1)
Moderate (3)	Windy (3)		
Warm (4)	A lot of wind (4)		
Hot (5)	Strong wind (5)		

The potentialities for thermal comfort can be computed utilizing Equation 1, which is:

$$\pi_j = \gamma_j - \gamma_{j-1} \quad (1)$$

Further explanation includes $\pi_j(X) = P(Y = j|X)$ which represents the probability of the value $Y = j$ given X for $j = 1,2, \dots, q$ and $\gamma_j(X) = P(Y \leq j|X)$ is the cumulative probability of the response variable category j for $j = 1,2, \dots, q$. The ordinal-scaled response variable Y is related to the probability vector $\pi = \left(\pi_1(X), \pi_2(X), \dots, \pi_q(X)\right)$. The logistic regression model estimation can be calculated to determine the probability of each comfort class according to Equation (2):

$$\pi(x) = \frac{e^{(\beta_0+\beta_1 x1+\beta_2 x2+\dots+\ \beta p x p)}}{1+\ e^{(\beta_0+\beta_1 x1+\beta_2 x2+\dots+\ \beta p x p)}} \quad (2)$$

The response variable Y is an ordinal scale variable with $\beta_i, i = 0,1,2, \dots .n$ are parameter generated from the calculation. The model above can be transformed into a linear function by formulating the response variable with the logit Equation (3):

$$g(x) = \ln\left[\frac{\pi_f(x)}{\pi_o(x)}\right] = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ik} \quad (3)$$

Where, $(x) = ln\left[\frac{\pi_f(x)}{\pi_o(x)}\right]$ is logit function. In ordinal logistic regression, odds are defined for each category $Y \geq j$ The cumulative odds obtained from software assistance are cumulative from the right, so the OR value in the equation describes that for every increase in predictor variable X_k by one unit, there is an increase or decrease in odds in the category $Y \geq j\,; j = 3,2,1$ multipicatively as much as exp (β_k). The definition of the Odds Ratio for the variable X_k is expressed in Equation (4):

$$OR_k = \frac{\frac{P(Y\leq j|X_k=x_k+1)}{P(Y>j|X_k=x_k+1)}}{\frac{P(Y\leq j|X_k=x_k)}{P(Y>j|X_k=x_k)}} \quad (4)$$

Table 3. Confusion Matrix

		Predicted label (j)				Row
		1	2	…	R	
Actual label (i)	1	n_{11}	n_{12}	…	n_{1R}	n_1
	2	n_{21}	n_{22}	…	n_{2R}	n_2
	.	.	.	.	.	.
	.	.	.	.	.	.
	.	.	.	.	.	.
	R	n_{R1}	n_{R2}	…	$n_{.R}$	n
	column	$n_{.1}$	$n_{.2}$	…	$n_{.R}$	n

Model Evaluation. The sample, consisting of 552 observations, underwent data splitting into training and testing sets. The data was divided into a 70% training set (386 data) and a 30% testing set (166 data). The data division was performed using random sampling to avoid bias towards different data probabilities. A confusion matrix [32] was employed to evaluate the ordinal-scaled model. The confusion matrix allows for the model’s conformity between predicted and actual value, as illustrated in Table 3.

The logistic regression model's performance is considered good if the diagonal elements of the confusion matrix have consistent coefficients for the actual (i) and predicted (j) values. The probabilities of i and j can be calculated using Equations (5) and (6). Several components resulting from the confusion matrix include True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Model evaluations such as Precision, Recall, and F1 Score. Precision is the correct prediction in that class divided into predictions categorized in that class. Recall is the correct prediction in that class divided by the actual category in that class. Meanwhile F1-score is an evaluation metric for a classification defined as the harmonic mean of precision and recall. Mathematically, it is expressed in Equations (7 - 9):

$$P_i = n_i/n \quad (5)$$

$$P_j = n_j/n \quad (6)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (7)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (8)$$

$$\text{F1 Score} = 2 * \frac{\text{Presicion x Recall}}{\text{Precision+Recall}} \quad (9)$$

Calculation of Modified Index. The initial approach to modifying a comfort index involves collecting daily climate data hourly. Data is collected from 09:00 to 15:00, aligning with the tourist visitation hours and ticket counter opening times at TMII. Data observation extends until 15:00, marking the end of tourist activities at TMII. Data collection spans from June 1 to August 31, 2023, concurrent with the questionnaire data. It is worth noting that research on index modification, such as the Tourism Climate Index (TCI), has been conducted previously. The calculated modification transforms the original daily climate data period into the morning-to-afternoon average. This decision is based on the observation that beach tourists typically do not visit in the afternoon [33]. The technique for modifying the thermal comfort index involves creating histograms using the Sturges rule [34] to avoid pitfalls in all data. This empirical method is used for determining the number of classes in a histogram. Each climate parameter, Normal Effective Temperature (TC), wind speed (W), cloud cover (A), and precipitation (P) is visualized using the histogram. The number of classes (k) and class intervals (i) can be expressed in Equations (10) and (11):

$$k = 1 + 3.322 \log n \qquad (10)$$

$$i = \frac{X_{max} - X_{min}}{k} \qquad (11)$$

Description of the statistical equation involves n, the number of data points, where each class interval is represented by i. The maximum value of the data is denoted as X_{max} and the minimum value is X_{min}. The purpose of constructing the histogram is to determine the data classes, frequencies, and data distribution. Specifically, for the NET parameter, it is calculated using a thermal comfort approach [35]. The calculation of effective temperature considers wind speed, air humidity, and average air temperature. Mathematically NET is calculated as in Equation 12:

$$NET = 37 - \frac{37 - T}{0.68 - 0.0014RH + \frac{1}{1.76 + 1.4v^{0.75}}} - 0.29T\,(1 - 0.01RH) \qquad (12)$$

Where, NET is *Normal Effective Temperature* in units of Celcius. T is average daily temperature and RH representative percentage average daily relative humidity. Other climate parameter for calculation NET is wind speed (m/s). The results of NET calculations produce temperature values that are lower than the average air temperature.

Tabel 4. Rating for sub-index HCI

TC (°C)	P (mm)	A (%)	W (km/h)	Rating
			>70	-10
	>25.00		-	-1
≥39	>12.00	-	50-70	0
≤-6	-	100	-	1
-1- -5 37-39	9.00- 12.00	91-99	-	2
0-6	-	81-90	40-49	3
7-10 35-36	-	71-80	-	4
11-14 33-34	6.00- 8.99	61-70	-	5
15-17 31-32	-	51-60	30-39	6
18-19 29-30	-	41-50	-	7
27-28	3.00- 5.99	31-40	0 20-29	8
20-22 26	<3.00	0	10-19	9
23-25	0.00	1-10 11-20	1-9	10

The second stage involves determining ratings and weights for each thermal comfort parameter. Ratings are assigned to each class value. The rating and weight values are assigned based on the researcher's perspective and subjectivity. The relationship between ratings and weights is inseparable, forming the index value ranging from 0 to 100. The detailed ratings and weights for the HCI-urban are presented in Table 4.

Finally, the modified index, based on class values, ratings, and weights, will be compared with the HCI-urban. This aims to assess how well the modified index captures specific events such as rainfall. The evaluation of both indices is calculated using the *Root Mean Square Error* (RMSE) and correlation, as indicated in Equations (13) and (14):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (13)$$

$$Correlation = \frac{\sum_{i=1}^{n}(x_i - \hat{x})(y_i - \hat{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \hat{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \hat{y})^2}} \qquad (14)$$

Where i start from June 1 until 31 August 2023. y_i is the modified index value and $\hat{y}_i$ is the HCI value Root Mean Square Error (RMSE) is used to find the difference between the modified index value and the HCI value. Meanwhile n represents the amount of data from variables X and Y X is the HCI value and Y represents the modified index value.

HCI Calculation. Thermal comfort information is presented through an index. The index in daily format is required for verification against questionnaire data. The index approach in this research utilizes the HCI-urban. HCI-urban has sub-indices, with the first being thermal comfort (TC). TC is calculated by involving climate parameters such as relative humidity, maximum temperature, average air temperature, and wind speed. The result of the TC calculation is called the Normal Effective Temperature (NET). Other components include aesthetic (A), precipitation (P), and wind speed (W). The aesthetic component is a climate consisting of cloud cover observed manually per hour. The calculation of HCI-urban from Scott [23] is shown in Equation (15):

$$HCI_{urban} = 4TC + 2A + 3P + W \qquad (15)$$

The weight proportions assigned to each sub-index are not uniform. The hierarchy of weights, arranged from the smallest to the largest, is W (1), A (2), P (3), and TC (4). TC holds the highest weight among all sub-indices. The weights generated by HCI are calculated through a survey spanning over ten years and visitor validation. Each HCI sub-index is assigned a maximum rating of 10 (optimal for tourists) and a minimum rating of 0 (hazardous conditions). HCI-urban also considers data availability, such as cloud cover. Cloud cover data is more readily accessible from meteorological stations than historical sunshine duration data. This is because not all meteorological stations possess sunshine duration data.

3. Result and Discussion

Age Distribution. The processing of questionnaire results includes (i) identifying the age distribution, (ii) comfort based on morning and afternoon time, and (iii) logistic regression model. The first analysis involves identifying the age distribution over 92 days for 552 respondents. Age data is calculated using histogram techniques to determine the frequency and classes for each location shown in Figure 3. The calculation results indicate nine age classes with an interval of 7 for each class. The varying frequencies affect the percentage values of these classes. The first-class boundaries represent the minimum value of the data distribution, while the upper boundaries of the final class represent the maximum value. Based on age grouping, the average ages for the three locations are 30 years (TMII), 25 years (KRB), and 34 years (TSI), respectively. The oldest respondents are recorded in TSI at 73 and 64 years in the other two locations. The highest age frequency falls within the 17–22 years range in KRB, reaching 70 individuals (38%). Meanwhile, in TSI, 29.3% (54 individuals) fall within the 24–30 years age range. The age frequency in the 22–27 years range is higher than the 17–22 years range in TMII, accounting for 21.7%. A relatively small percentage of TMII falls within the 58–64 years age range, at 3.2% (6 individuals). The number of ages in the final class is one person each in KRB and TSI, with a percentage of 0.5% in both locations. The 37–43 age class in TMII has the same rate (9.2%) as the 48-54 years class in TSI.

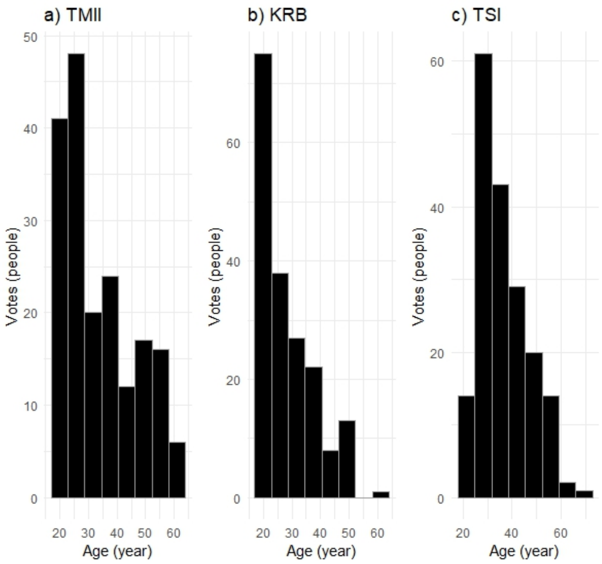
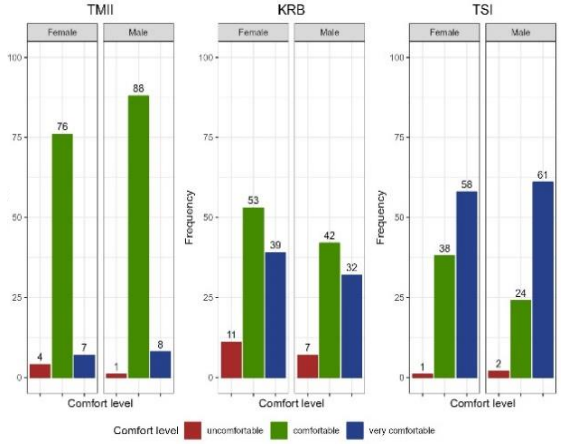
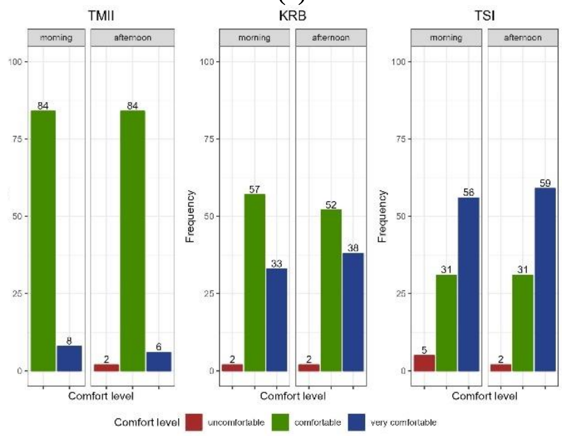


Figure 3. Histogram of respondents' ages



(a)



(b)

Figure 4. Perceptions of thermal comfort based on gender (a) and time (b) Comfort based on time

Gender-based comfort analysis. Comfort based on gender is identified at each location. The number of perceptions for the three categories is presented in Figure 4. The number of males and females in the three places is not equal. Assessments of comfort levels also vary from one another. Overall, the percentage of 'comfortable' perceptions between males and females in TMII is 88% and 93%, respectively. The quantitative results indicate that female visitors are more comfortable, at 92% (81 individuals), compared to males. Assessments of 'uncomfortable' and 'very comfortable' perceptions are given by males at 2% (2 individuals) and 10% (8 individuals), respectively.

Thermal comfort assessments for the three categories emerge at KRB and TSI. KRB, with its higher topography compared to TMII, has different comfort perceptions. Sixty-five female visitors (63%) in KRB give the most 'very comfortable' perceptions. This high percentage is notably different from the perceptions given by males. The percentage of males, on the other hand, feel more 'comfortable' (47%) and 'uncomfortable' (16%), which is relatively larger than females. The gender difference in the 'uncomfortable' level is only four individuals. In contrast to KRB, TSI has a percentage of 'very comfortable' perceptions by females at only 60%. This percentage has a difference of 7% from males. The number of perceptions for males and females in TSI is the same, namely 58 individuals. Other categories show that 34 females (35%) state 'comfortable,' followed by 'uncomfortable' with five individuals (5%). If the 'uncomfortable' level in TSI is compared between males and females, females tend to feel 'uncomfortable' more. Based on the existing percentages, 'very comfortable' perceptions are more frequently given in TSI compared to the other two locations. Differences in perception results can provide input to tourism managers in maintaining environmental components. Based on the comfort perception, vote results show that both men and women feel comfortable in locations with low (cold) temperatures.

The identification of comfort based on the division of morning and afternoon time is presented in Figure 2b. The analysis of 184 respondent data in TMII shows that 168 individuals feel Comfortable (91.3%) in the morning and afternoon. 'Uncomfortable' responses occur in the afternoon with two individuals (2.2%). In the morning, TMII visitors provide assessments ranging from 'comfortable' to 'very comfortable.' There are no assessments of discomfort during the morning at TMII. The 'very comfortable' category is also felt by eight individuals in the morning and afternoon. Analysis of respondents in KRB shows that 57 individuals feel 'comfortable' in the morning (62%) and in the afternoon (56.5%). 'Uncomfortable' responses occur in the afternoon with 2.2% (2 individuals). The total number of respondents in the afternoon who feel 'very comfortable' is 38.

Table 5. Partial and simultaneous test output

Variable	Std err	p
Temperature	1.043	0.001
Wind	0.506	0.314
Cloud	1.016	0.101
Rainfall event	2.673	0.000
Duration	1.080	0.314
Activity	-0.643	0.527
Gender	0.879	0.351
Shirt	-0.687	0.484
Frequency	-0.679	0.488
Pseudo R-squ		63.2%

Table 6. Comparison of coefficient estimates and odds ratios

Variable	Coef	Odd ratio
Temperature	3.476	32.33
Wind	-0.508	0.60
Cloud	-1.665	0.19
Rainfall event	-11.66	0.00
Duration	1.080	2.94
Activity	-0.643	0.53
Gender	0.879	2.41
Shirt	-0.687	0.50
Frequency	-0.679	0.51

The 'uncomfortable' category is also felt by tourists in both the morning and afternoon (4.4%). The perception of 'very comfortable' in TSI differs between the two locations. Fifty-nine respondents (64%) perceive it as 'very comfortable.' This number is only a difference of 3 respondents in the morning. The perception of 'comfortable' in the morning and afternoon has the same number, namely 31 individuals. As for the 'uncomfortable' ratings in the morning and afternoon in TSI, there are five individuals and two individuals, respectively. Generally, perceptions of 'uncomfortable' to 'very comfortable' for all three tourist locations can occur in the morning and afternoon, except in TMII. Based on observations at tourist attractions, if visitors feel uncomfortable in the morning, they still accept and enjoy their vacation. However, if the discomfort arises during the day, visitors rush home, especially if it rains in the late afternoon. Some respondents state a level of 'uncomfortable' due to rain. The occurrence of rain impacts two things: a negative assessment of the comfort of tourism and other activity options to fill the lost time [36].

Logistic Regression. Initially comprising three categories, the response variable was simplified into 'uncomfortable' and 'comfortable.' The dataset consists of 29 instances categorized as 'uncomfortable' and 523 as 'comfortable.' For the training data, 19 cases were labeled 'uncomfortable,' and 367 were marked 'comfortable.' The testing data includes ten instances of 'uncomfortable' and 156 for 'comfortable.' Data splitting was performed randomly. The results of the partial and overall tests are presented in Table 5. The logistic regression model can explain 63.2% of the variation in the data. Positive coefficients are observed for the predictors of temperature, duration, and gender. However, none of the five non-climatic factors show significance with a p-value < 0.05, indicating that all non-climatic parameters do not influence thermal comfort.

On the contrary, significant p-values < 0.05 are found only for the predictors of climatic parameters—precisely, temperature and rainfall, with values of 0.001 and 0.000. Interpreting the model can be conducted after the completion of odd ratio calculations. The estimated coefficient values and odd ratios are presented in Table 6.

The model comparisons for each class are multiplicative, with the baseline model being class 1. The temperature variable in the odd ratio class 0 indicates that with a one-point increase in temperature, the likelihood of a shift tends to increase by 32.3 from the 'uncomfortable' to the 'comfortable' category. In other words, warmer temperatures are inclined towards the 'comfortable' category. Visitors generally feel comfortable at a thermal temperature (TC) of 22.7°C - 28.0°C with wind speed conditions of 2.47 km/h - 8.02 km/h. Additionally, visitors will feel uncomfortable at tourist locations if it rains, whether light rain or moderate rain. This results in reduced vacation time.

Rain events have an odds ratio value of 0.01, which means that if it rains, visitors are 99.9% likely to feel discomfort. Factors forming thermal comfort based on the variables above, such as rain events, can be analyzed further. The amount of rain has a different intensity from one location to another. Rain events occurred from June 1 to August 31, 2023, at TMII, KRB and TSI, respectively, eight times, 19 times and eight times. Descriptively, the highest rainfall recorded in KRB was 78.8 mm on June 19. Compared with the other two locations, TMII is 35.5 mm, and TSI is only 11.5 mm. This rain event directly impacted the response of visitors who came.

Weather conditions significantly affect emotions and perceptions, such as the onset of rain, which can trigger emotions and frustration due to shortened vacation time, leading visitors to experience discomfort during their trips [36]. The temperature sensation variables, cloud cover and wind speed do not directly affect thermal comfort in the three locations. This result contrasts previous research stating that temperature and solar radiation mutually influence comfort [37]. Sufficient vegetation cover in an area can give a comfortable impression. Outdoor tourism in tropical areas requires canopy coverage, such as trees reaching pedestrian areas, to prevent direct exposure to solar radiation [38].

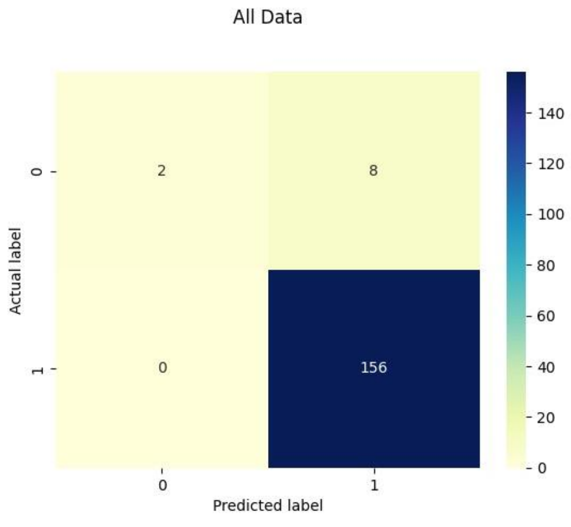


Figure 5. Confusion matrix

Table 7. Classification report

	Precision	Recall	F1-score	Support
1	1.00	0.20	0.33	10
2	0.95	1.00	0.97	156
Accuracy			0.95	166

Model Evaluation. The model's performance is depicted in a confusion matrix for the classification of each class. The matrix contains values illustrating the model's performance, aiming to measure the algorithm's performance across two or more categories. Testing data is classified into the model matrix. Rows in the matrix represent the predicted values for each class, while columns represent the actual values of the data. Label 0 denotes the category 'not comfortable,' whereas the category 'comfortable' is labelled as 1. Based on the testing data of 166 records, the model correctly predicted the 'comfortable' category at a rate of 93.9% (156 records), while only two were correctly predicted in the 'not comfortable' category. The results of the confusion matrix are presented in Figure 2. The performance metrics, including accuracy, recall, and F1-Score, are shown in Table 7. The model exhibits an accuracy of 95%, indicating excellent data classification. Furthermore, the precision of the model in predicting positive classes for 'uncomfortable' and 'comfortable' is 100% and 95%, respectively. Meanwhile, the recall values are 20% for the 'uncomfortable' class and 100% for the 'comfortable' class. The model balance (F1-Score) for the 'uncomfortable' and 'comfortable' classes is 33% and 97%, respectively.

Modification of Thermal Comfort Index. The initial stage in modifying the climate comfort index is time series analysis. The aim is to find out the distribution of data and statistical values. Time series analysis was carried out from 2008 to 2022 from daily data at the TMII location. The data format analyzed is in the form of daily averages for air temperature, effective temperature, air humidity and wind speed. Meanwhile, rainfall is calculated from the daily total. In general, the climatic parameter profile in TMII exhibits fluctuations over time, as depicted in Figure 6. The maximum value of the average temperature over 15 years is 31°C, with the recorded minimum being 23.5°C. Fluctuations in the average air temperature values are followed simultaneously by effective temperature. In the context of effective temperature calculations, the results will be lower than the average air temperature.

The average wind speed in TMII is 2.7 km/h, with the maximum wind speed occurring more frequently in November 2008, January 2009, November 2009, January 2010, and January 2011, reaching a value of 16.67 km/h. Rainfall is not analyzed in the context of extreme analysis but only presents class intervals of low rainfall over 15 years. The maximum daily rainfall in TMII (East Jakarta) occurred on January 1, 2020, amounting to 377.2 mm. The peak of the rainy season in TMII occurs during the December-January-February (DJF) period. Another analyzed parameter is air humidity. The fluctuation of daily average air humidity values is quite diverse. Furthermore, the air humidity in TMII is 78.5%. Air humidity is also considered in calculating the effective temperature, so data availability in creating the thermal comfort index must be complete.

Histogram analysis of TMII is conducted to determine the statistical distribution of data. The format and data parameters in the histogram analysis are the same as for time series data. Statistically, histograms facilitate the creation of classes for each climatic comfort parameter. Each class has an interval value based on calculating the maximum and minimum values. Histograms for each parameter are displayed in Figure 7. There are two types of data distribution: normal and gamma. NET, wind speed, and air humidity parameters follow a normal distribution, while rainfall falls into the gamma distribution category.

Wind speed in TMII, with a frequency of 17.9%, occurs at speeds ranging from 0 to 4 km/h, with an event frequency of 1967 occurrences. Indicates that low wind speeds are typical in TMII. The Effective Temperature (NET) in TMII ranges from 24.5°C to 25°C (1022 occurrences). Air humidity also follows a normal distribution, similar to wind speed and NET parameters. The proportion of air humidity in the 75%-80% class in TMII is 24.7%, with a class interval of 6. This implies that moisture is still relatively high. One of the gamma distributions is rainfall. The frequency of low rainfall events dominates the TMII region. 73.8% of rainfall is mainly dominated by 0 mm -10 mm, with a frequency of 4045 occurrences. Meanwhile, 83.8% of the frequency of rainfall events is 0 – 20 mm, 4594 times.

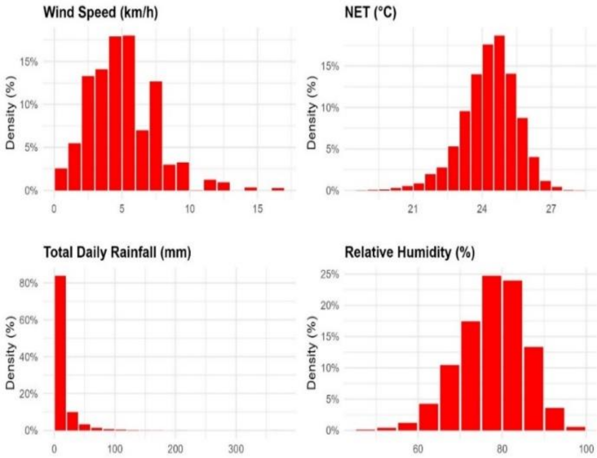


Figure 7. Histogram of thermal comfort parameter

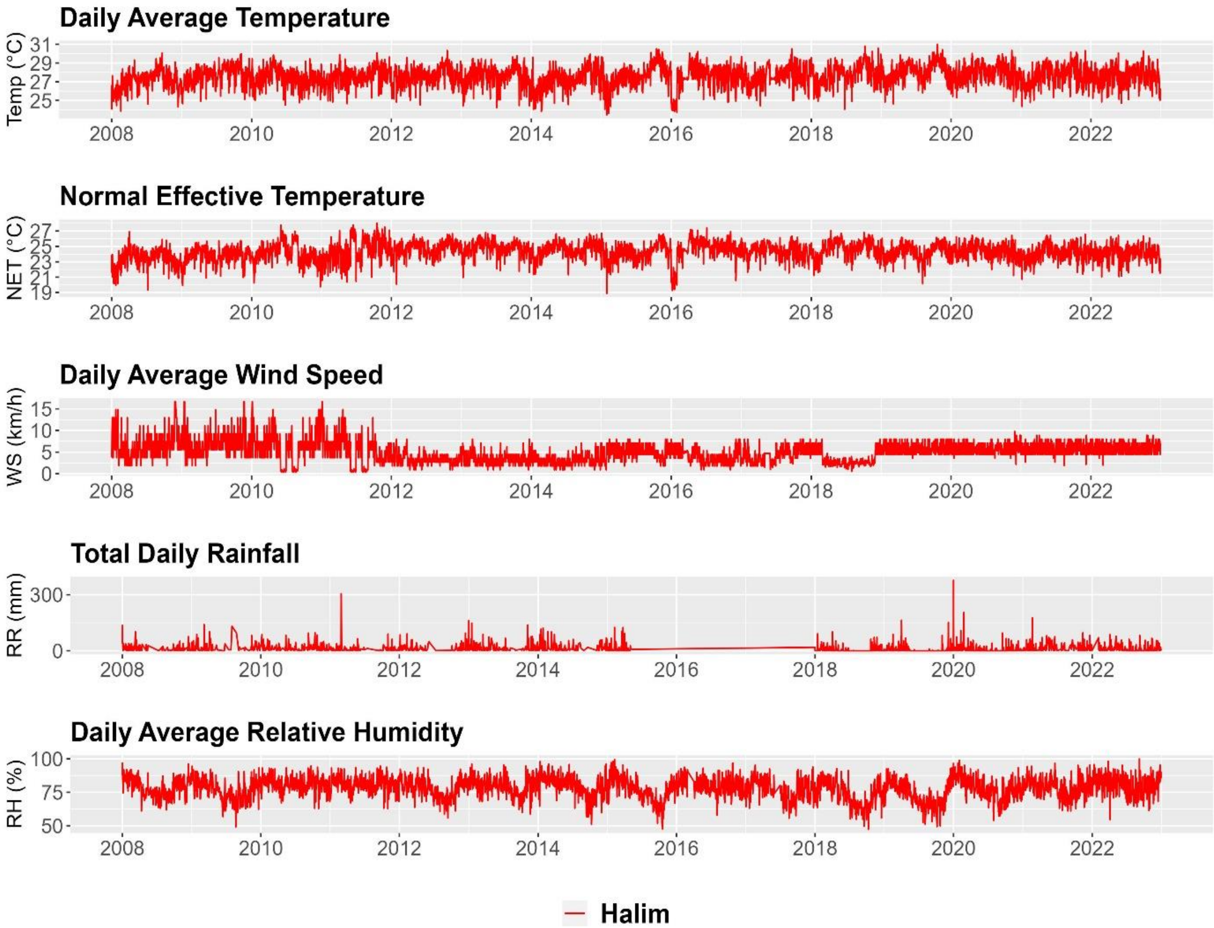


Figure 6. Profile of daily climatic parameters from 2008 to 2022

Table 8. Rating for each sub-index derived from the modified thermal comfort index

TC (°C)	P (mm)	A (%)	W (km/h)	Rate
19-20.9	0-0.49	95-100	0-0.99	10
21-22.9	0.5-0.99	86-94.9	1-1.99	9
23-24.9	1-1.49	77-85.9	2-2.99	8
25-26.9	1.5-1.99	68-76.9	3-3.99	7
27-28.9	2.0-2.49	59-67.9	4-4.99	6
29-30.9	2.5-2.99	50-58.9	5-5.99	5
≥31	3.0-3.49	41-49.9	≥6.00	4
-	3.5-3.99	32-40.9	-	3
-	4.0-4.49	23-31.9	-	2
-	4.5-4.99	14-22.9	-	1
-	≥5	<14	-	0

The results of the rainfall histogram show that low rainfall can be the basis for creating thermal comfort classes. The limit for the total amount of rainfall to be considered is, at most, 10 mm. The thermal comfort parameters for thermal comfort modification are effective temperature, cloud cover, wind speed, and rainfall. The results of the histogram calculation by combining data are presented in Table 8. One of the thermal comfort components is the effective temperature. The class intervals and ratings for each parameter are not the same. Mathematically, the effective temperature is lower than the average air temperature. There are seven classes for the effective temperature parameter with a class interval of 1.9 °C. The lowest rating for the effective temperature is at temperatures greater than or equal to 31°C, which is 4. The rating value for the effective temperature increases by 0.1 with the addition of classes up to 31°C. The class with the highest rating is in the temperature range of 19-20.9°C, which is 10.

Other parameters, such as rainfall, are restricted to values above 5.00 mm. Rainfall and cloud cover components are structured into 11 classes. A maximum rating of 10 is assigned to total rainfall up to 5 mm. This rating of 10 is based on the assumption that higher rainfall would decrease the comfort level for visitors. The sub-index of cloud cover has intervals in each class, specifically 9.9%. The minimum rating is assigned to cloud cover less than two octas (<14%). The comfort condition is present in cloud cover of 4 to 8 octas. Cloud cover provides a sensation of warmth that is not directly felt by the skin due to the presence of a barrier. The sub-index for wind speed has the same classes as the effective temperature, namely seven classes. Low wind speed profiles are given a maximum rating of 10.

In essence, assigning weights will result in the maximum value of an index. The maximum rating for a sub-index indicates the multiplier value against the weight. Simply put, the higher the rating value, the closer it will yield the optimum value of 100 for the index. The modified weights differ from the HCI-urban. The TC and P components have the same weight, namely 4. Meanwhile, the weights for A and W are one each. The results of modifying the thermal comfort index are presented in Equation 16 as follows:

$$\textit{Modified index} = 4TC + A + 4P + W \quad (16)$$

Changes in weight in index modification refer to the HCI: urban equation (Equation 14). Weight adjustments are made to produce comfort value limits according to visitor perceptions. The TC and W sub-indices have no change in weight. Weight changes were made to the cloud cover (A) and rainfall (P) sub-indices. The cloud cover sub-index has been changed from two to one. Meanwhile, the weight for the rainfall sub-index was increased to four. The basis for increasing weight on rainfall is that rainfall affects aspects of thermal comfort. Changes in the weight of the cloud cover and rainfall sub-indices are limited from values one to four manually.

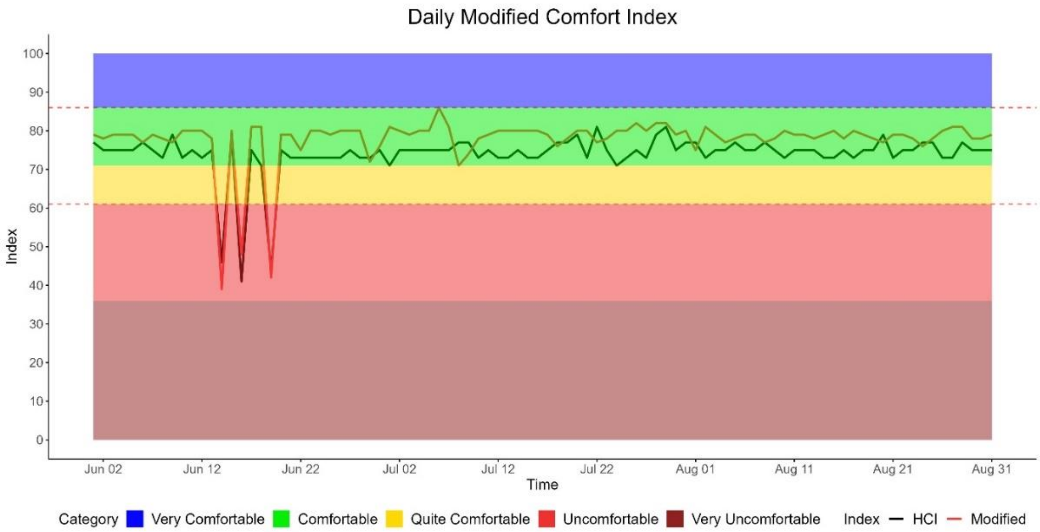


Figure 8. Daily modified comfort index period 1 June – 31 August 2023

Table 9. Comfort class categories based on values from the modified thermal comfort index

Category	Value
Very comfortable	86.00 – 100
Comfortable	71.00 – 85.99
Quite comfortable	61.00 – 70.99
Uncomfortable	36.00 – 60.99
Very uncomfortable	0.00 – 35.99

The modified comfort index values resulting from the rating and weight are displayed in Figure 8. The time series graph shows index values on average for daily periods (09:00 – 15:00). The modified index results exhibit varying values over time. During the period from June 1 to August 31, values range from minimum to maximum. Values below 50 occurred on June 14, June 16, and June 19. The index values for these times are 39, 48, and 42, respectively. The analysis indicates that index values are influenced by rainfall exceeding 5 mm. The HCI-urban index value on June 16 is lower than the modified index. This is due to daily rainfall 35.8 mm, resulting in an HCI-urban values 41. Rainfall on that date was 16 mm, 35.8 mm, and 17 mm. Rainfall events directly affect tourists' comfort perceptions. This impacts the assessment of the P rating by 0. Higher total rainfall on that day will reduce the comfort index value. Meanwhile, the effective temperature, wind, and cloud cover values on that date were quite good, indicating no extreme events.

The modified index categories were divided into five, from very uncomfortable to very comfortable are presented in Table 9. The simplification of the comfort category aims to simplify the upper and lower limit values for each class. The limit for the 'comfortable' category in the modification index is 61 – 70.99. Compared with HCI: urban, the comfortable value limit is 40 [23]. The difference in comfort value limits is caused by several factors, one of which is visitor sensitivity to rain events. Based on the analysis of 552 respondents, it was found that rain with light or moderate intensity would give an uncomfortable rating. The difference between ratings and weights in HCI: Urban has not fully represented the thermal conditions in tropical regions. Light rain events (<3.00 mm) give a rating of 9. Meanwhile, the modified index is rated 5 for rainfall <3.00.

Analysis of other components such as cloud cover has ratings of 7, 10, and 9 for the respective dates. High ratings are also observed for other comfort components like TC and W. The index values above 70 are observed from June 22 to August 31. During this period, it tends more towards the 'comfortable' category. The optimum value occurred on July 6, 2023, at 86. There was no rain on that date, and the effective temperature was 26.8 °C. Other data, such as wind speed, was only at a 1.28 km/h value, which falls into the calm wind category. Furthermore, statistical analysis results show that the correlation between the modified index and HCI-urban is 86%, with a standard deviation of 6.6.

The next step is to verify the results of the modified index against the visitors' responses during the daytime. The number of respondents during the day is 92 people. Choosing respondents during the day represents the perception of comfort on that day. A comparison of the categories from the modified index, HCI, and respondents' perceptions is shown in Figure 6. The comfort class categories of HCI, which number 8, are simplified into three classes: 'very comfortable,' 'comfortable,' and 'uncomfortable.' Based on the perceptions collected at TMII, it is evident that no visitors feel 'very comfortable.' Respondents choosing the 'comfortable' condition are 87 people. This number is only different by one from the modified index. Looking at the 'uncomfortable' class, five respondents and three are from the modified index. Meanwhile, for HCI, no values fall into the 'very uncomfortable' category for the three months. However, more assessments are in the 'comfortable' class, with a small portion in the 'very comfortable' class.

The difference between HCI results and respondent perceptions is attributed to HCI's 'uncomfortable' category threshold. Discomfort assessed by HCI falls within the range of -9 to 39. This range is too narrow, making discomfort responses dependent on extreme climate data. The rating for the rainfall sub-index (P) in HCI evaluates rainfall between 6 mm and 8.99 mm with a high rating. Meanwhile, respondents' perceptions in tropical regions consider rain discomforting tourism. In the context of the rainfall sub-index (P) rating, the modified index aligns the daily rainfall rating with the modified TCI index results. Although the TCI modification is applied monthly, this range can serve as a basis for daily ratings [23]. Analysis of another sub-index, namely effective temperature, also yields different ratings compared to HCI-urban. HCI-urban rates temperatures in the range of 23°C – 25°C as 10 (very comfortable). Meanwhile, the modification places temperatures in the 23°C–24.9°C with a rating of 8, categorizing it as 'comfortable' [38]. Furthermore, the wind speed (W) and cloud cover (A) sub-indexes differ from HCI-urban. The wind speed values and ratings given in HCI align with the Climate Index for Tourism (CIT) based on respondent perceptions, considering the ideal conditions to be 1-9 km/h [39].

The difference in cloud cover rating assessments between the modified index and HCI-urban is visitor perceptions. HCI-urban, HCI-beach, and the optimization index provide assessments opposite to the modified index in tropical regions [33]. These three indices believe that more cloud cover will reduce the rating. It is important to emphasize that the location of the tourist destination will influence visitor perceptions for each sub-index. It is unavoidable that tourists in urban areas tend to prefer green areas dominated by nature tourism.

The performance evaluation of HCI and TCI scores in coastal areas was correlated with the average number of monthly visitors [33]. The results show a high correlation with the modified index. However, this method cannot be applied to this research because magnetism or the desire to travel only sometimes considers weather and climate conditions except during the rainy season. The three locations studied were three months into the dry season in 2023. In addition, there is a school holiday calendar, which causes peak holidays in that period to be high.

Modifications to the comfort index only approach visitor perceptions by adjusting the rating values and weights from HCI: urban. The HCI: urban sub-index is considered to have a threshold different from tropical areas. Qualitatively, the performance of the modified index with HCI: urban has differences in determining the uncomfortable and very comfortable categories. However, both indices performed well in determining the comfort category and were validated during the dry season (JJA); therefore, because there are still visitors who feel uncomfortable while on holiday during the dry season, they can make suggestions to tourism managers to sustain environmental comfort.

4. Conclusion

In broad strokes, this research contributes two essential aspects related to the perspective of the climate index in the tourism sector situated in tropical regions:

1. Climate factors influencing thermal comfort in urban tourism are temperature and rainfall. There is no correlation with gender, activities, duration, frequency, and clothing type in the context of comfort tourism.
2. A novel empirical methodology approach focuses on a modified climate index designed explicitly for humid tropical urban tourist. Modified index scores for each category are adjusted to better align with visitor votes.

The modified index approach is grounded in visitor perceptions at tourism locations. The modified index represents optimal values up to 100, similar to HCI-urban. In numerical calculations, the modified index comprises four sub-indexes calculated from the average climate data between 09:00 and 15:00. The modification technique, altering ratings and weights, effectively captures rainfall events from June to August. Furthermore, the index values for each category are adjusted to better align with visitor perceptions. A score of 60 on the HCI is in the comfortable category, but this value does not necessarily indicate comfort. However, when validated against respondent data, it is perceived as 'uncomfortable.' The occurrence of low to moderate-intensity rain has an impact on respondents' comfort. Adjusting category value ranges effectively evaluates the 'uncomfortable' and 'comfortable' categories. This study contributes value to thermal comfort assessment in tropical regions and preferences for using HCI-urban to assess thermal comfort perceptions.

Suggestion

Objectively, this research necessitates further development in terms of data validation. The data validation period should be extended by one year because it is crucial to continuously assess the index’s performance during dry and rainy seasons. Further research will evaluate HCI-urban in the rainy season and compare perception tourism. The next step will be analyzed using historical climatological data to modify the thermal comfort index comprehensively.

Acknowledgement

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