Vol. 66: 49–63, 2015
doi: 10.3354/cr01327

CLIMATE RESEARCH
Clim Res

Published October 6

Modeling tourism climate indices through fuzzy logic

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ABSTRACT: This paper proposes a fuzzy-based climatic index for tourism to reconcile imprecise linguistic terms with the computational rigor required by index calculations. A fuzzy logic-based inference engine contains IF–THEN fuzzy rules that are codified based on self-reported tourists' perceptions. Fuzzy logic helps to translate linguistic expressions of tourist perceptions of weather conditions into a score on the 7-point-scale Climate Index for Tourism (CIT). Fuzzy-based CIT was tested with data elicited from tourists, coming from a variety of climate regions, who visited the beaches of North Cyprus. Statistical analyses confirmed cross-cultural differences related to perceptions of favorable climate. Fuzzy-based CIT functions as a useful tool for calculating the climate attractiveness for tourists, which can be considered as a practical implication for tourism destination management.

KEY WORDS: Fuzzy-based Climate Index for Tourism · Cross-cultural differences · Linguistic expression

1. INTRODUCTION

As a climate-dependent industry, tourism is strongly affected by climate (Amelung et al. 2007). From the supply-side perspective, climate influences tourism site selection, the efficiency and application of infrastructure, benefits for the commercial sector, and the schedule of tourist activities (Gomez-Martín 2005). However, climate is also a significant indicator of demand-side (tourist) behaviors (De Freitas 2015). Climate affects tourists' decision-making process in their selection of destination, length of stay, comfort, satisfaction, and loyalty (Hernández-Lobato et al. 2006, De Freitas et al. 2008, Denstadli et al. 2011, Becken 2013, Romão et al. 2014, De Freitas 2015). Tourists tend to evaluate the attractiveness of the climate of a destination with a minimal level of uncertainty (Chew & Jahari 2014). Consequently, creative and adaptive strategies are needed to mitigate the undesirable consequences of weather (Weaver 2011, Kaján & Saarinen 2013, Olya & Alipour 2015).

To provide an accurate assessment of the temporal and spatial variations of climatic suitability for tourism, a number of methods and metrics have been developed and applied. De Freitas (1990) conceptualized climate as the thermal, physical, and aesthetic facets of on-site atmospheric conditions, which together create an enjoyable setting for tourism activities. A range of studies has focused exclusively on the thermal aspect, applying several sophisticated thermal indices for assessing human comfort regarding tourism (e.g. Matzarakis et al. 1999, Cegnar & Matzarakis 2004, Ibarra 2011). Predicted Mean Vote and Physiologically Equivalent Temperature are examples of indices that have been successfully applied. Other studies have used more integrated and multifaceted indices for climate assessments in the context of tourism (e.g. Becker 1998, Gómez-Martín 2006, Amelung et al. 2007, Scott et al. 2008, Perch-Nielsen et al. 2010, Deniz 2011). The most commonly used index in this type of analysis is the Tourism Climatic Index (TCI) proposed by Mieczkowski (1985).

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An important strength of the TCI is that it incorporates all 3 of De Freitas' (2003) facets of tourism climate. However, a number of limitations have also been identified, including a sophisticated weighting and rating system, failure to consider the potential overriding effects of rain and other weather elements, and a lack of empirical validation of the index (Morgan et al. 2000, De Freitas et al. 2008, Moreno & Amelung 2009). Index values based on self-reported tourist preferences are known to be more reliable indicators of climate attractiveness than those based solely on expert judgment. To improve on this point, Morgan et al. (2000) used survey results on climate preferences to adjust the weighting and rating scheme of Mieczkowski's index. The surveys were administered on beaches in Wales, Malta, and Turkey. Differences in climate preferences were reported but were not specifically linked to culture.

De Freitas et al. (2008) proposed a new generation of TCI named Climate Index for Tourism (CIT) that addressed some major deficiencies of past indices. At the heart of this CIT typology matrix lies the integration of the thermal, aesthetic, and physical aspects of weather conditions while considering the overriding effects of some weather aspects. The rating of the various weather types is based on empirical information and can therefore be easily adapted to specific activities or locations. Cross-cultural differences in climate satisfaction have been treated in several previous studies (Gómez-Martín 2006, Rutty & Scott 2015), but mostly these were mentioned as a direction for future research (De Freitas et al. 2008). The dependence of CIT on empirical information makes it a data-intensive tool with limited appeal and applicability. As a result, TCI-based analyses still appear next to CIT-based studies despite the conceptual and methodological superiority of the CIT approach.

The stronger empirical foundation of tourism climate indices has become an important development in recent years. However, this development has been accompanied by new challenges. Collecting information related to climate preferences requires the use of everyday terms to describe weather aspects, such as 'warm,' 'cold,' 'sunny,' and 'cloudy.' Tourists tend to find these terms easy to interpret; however, they cannot be fed directly into a computer model. For both TCI and CIT, linguistic expressions related to weather sensations need to be translated into numerical terms by an expert. The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) thermal sensation scale (Gagge et al. 1986) constitutes a step in this direction; however, a mechanism is needed to acquire tourists' preferences in the context of linguistic variables, and then transform these into numbers to enhance the accuracy of climate variable integration as a typology matrix, and eventually translate the numerical output into intelligible linguistic terms. In this paper, we propose to bridge the gap between words and numbers using a mathematical approach (fuzzy logic), which has the following distinct advantages (Novák 2006, Zadeh 2008):

- It supports the use of linguistic variables in a mathematical model.
- It allows imprecise facets of weather to be transformed into precise numerical values; in other words, fuzzy logic alleviates the random and uncertain properties of weather parameters, which is helpful in decision making and tourism management.
- It permits the use of fuzzy thresholds for weather facets, which is useful when considering cross-cultural differences in weather preferences.
- Its rule base can be easily modified and can empower fuzzy logic as a modeling language that can address the overriding effect of meteorological parameters (e.g. rainfall and wind) in the formulation of the TCI.
- It simplifies knowledge acquisition and representation and reduces the dependence of tourism activists on experts for the estimation of the favorability of climates for tourists. However, the CIT functions based on tourists' declarations, and an expert is still needed to estimate CIT values.

This research contributes to the knowledge of tourism climate in several ways. First, a technical method was developed using the aforementioned advantages to address the drawbacks of previous approaches, especially those related to cross-cultural differences. Second, it addresses cross-cultural aspects of tourism climate, which to our knowledge have not previously been statistically demonstrated. Finally, the modeling of the TCI, using fuzzy logic systems and matrix laboratory (MATLAB) software, helps to transform the tourism–climate nexus from theory to practice. Accordingly, we discuss managerial implications and provide direction for further studies.

2. THEORETICAL FRAMEWORK

Our research approach is interdisciplinary and is contextualized based upon 2 concepts/theories. The first concept is CIT, which indicates the range of the climate parameters for beach activities, specifically 'sun, sea, and sand' (3S) holidays. 3S tourism is the main product that motivates tourists who are seeking warm climates to indulge in tanning under the sun (Obrador et al. 2009). Long and dry summers with the distribution of precipitation within a few months in the mild winter are perfect conditions for 3S tourism (Andronikou 1987). This form of tourism has been a dominant mode since the 1950s and 1960s, with seasonal concentrations along the coastal areas of the Mediterranean, Caribbean, Adriatic, Aegean, and many islands in the Pacific, to name a few (Koutra & Karyopouli 2013, Trias et al. 2014). Weaver (1993) stressed the resistance of 3S tourism as a popular tourism product on small islands, which in all likelihood would not be substituted by other products/services. North Cyprus is a Mediterranean island with a suitable climate that generates calm seas and stable beaches, and climatic facets, except precipitation, do not function as sources of risk toward 3S tourism (Olya & Alipour 2015). The second concept is fuzzy logic theory, which is elaborated in the following sections.

2.1. CIT

CIT, which was devised by De Freitas et al. (2008), is a multifaceted indicator of hospitality and recreation that rates weather/climate along a favorable–unfavorable spectrum. CIT is defined as follows:

$$\mathrm{CIT} = f[(\mathrm{T}, \mathrm{A}) \times \mathrm{P}] \quad (1)$$

It is a weather typology matrix that is composed of thermal (T), aesthetic (A), and physical (P) facets that determine a climate concurrence range rated from very poor (1 = unacceptable) to very good (7 = ideal). T is defined based on physiological and environmental thermal variables (such as heat loss by evaporation, wind convection, exchange of long radiation, metabolic heat, and solar heat load). These parameters affect the body–atmosphere energy balance. To maximize the flexibility of the index, the ASHRAE scale is used to express thermal sensation on 9 levels, ranging from 'very cold' to 'very hot.' Facet A indicates the beauty of the sky (including the degree of cloudiness), and P refers to the physical aspects of climate, such as wind and precipitation.

2.2. Fuzzy logic theory

Fuzzy logic theory was developed by Zadeh (1965) as a way of expressing uncertain information in a mathematical form. The main idea underlying fuzzy logic is 'that it allows for something to be partly this and partly that, rather than having to be either all this or all that' (Kişi & Tombul 2013, p. 204). Similarly, Novák's (2006) noted fuzzy logic deals with reasoning that is approximate rather than fixed and exact. Fuzzy logic does not consider binary sets in which variables may take on true or false values; its variables may have a truth value that ranges in degree between 0 and 1. Kişi & Tombul (2013, p. 204) presented the following description of fuzzy logic: 'In the fuzzy inference method, a set of input data along with the corresponding outputs are introduced to the fuzzy system.'

Furthermore, when linguistic variables are used, these degrees may be managed by specific functions. Fuzzy logic is typically implemented in a fuzzy system, which can 'learn' how to transform a set of inputs into an optimal set of outputs via a fuzzy associative memory (Kosko 1993). The heart of a fuzzy system (see Fig. 1) consists of a fuzzy inference engine, which transforms (fuzzified) inputs into (defuzzified) outputs. The engine is driven by rules from the fuzzy rule base, which represents current knowledge about the relationship between inputs and outputs. Input and output variables and rules that trigger the fuzzy inference engine can be represented in linguistic terms that are meaningful to the outside world.

Fuzzy logic systems (FLSs) have been utilized in various fields, including electrical, civil, computer, natural resource, geology, and environmental engineering, to name a few (Demicco & Klir 2003). Recently, a number of applications of climate-related issues have been reported. Kişi & Tombul (2013) concluded that a fuzzy-genetic approach is able to provide a precise estimation of monthly evaporation in Turkey. Jeong et al. (2012) used a neuro-fuzzy model to forecast monthly precipitation. According to Özger et al. (2012), the application of the wavelet fuzzy logic model to address the lack of soil moisture helped to monitor network problems related to esti-

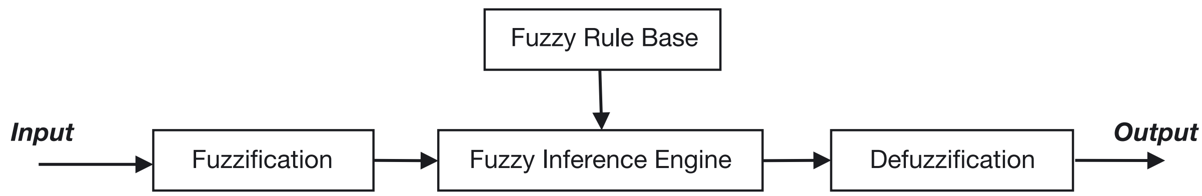


Fig. 1. Typical scheme of a fuzzy system (Kişi & Tombul 2013)

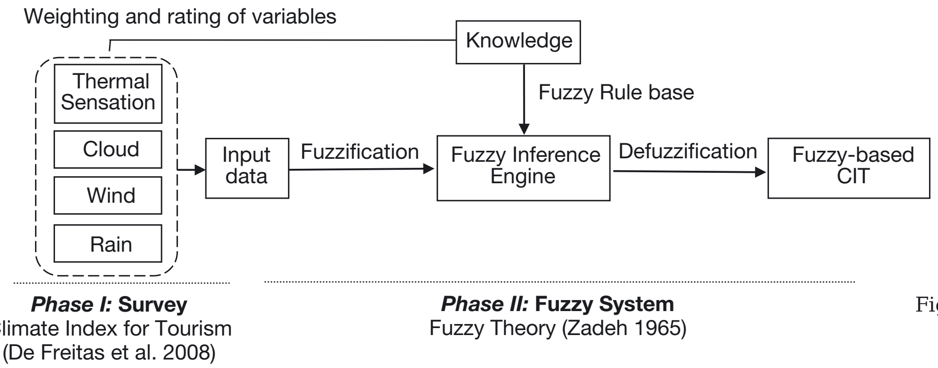


Fig. 2. Research design used in this study

mating the Palmer Drought Severity Index (PDSI) based on meteorological data (precipitation, temperature, soil moisture, and the previous PDSI value). Fuzzy logic was also employed by Prato (2010) to account for the uncertainty regarding ecosystem elements and the potential effects of climate change on ecosystem resilience and ecological integrity.

Our study is the first attempt to apply FLS to the assessment of CIT and to analyze its ramifications for the tourism industry with a focus on 3S tourism. Although in its infancy, as previously stated, some authors have investigated the application of fuzzy logic to the study of climate dimensions (Salgado & Cunha 2005, Nayak et al. 2007, Real et al. 2010).

Tourism preferences and perceptions vary from culture to culture. For instance, a very high temperature has a different meaning for a Russian tourist than it does for an African tourist. Fuzzy logic assists in the process of interpreting natural events, which have an uncertain threshold. According to De Freitas (1985), the 32.26–33.35°C range is considered 'slightly warm.' This means that if the temperature increases or decreases by 0.01°C, the level of thermal sensation changes to 'Warm' or 'Indifferent,' respectively. It is apparent that, in the real world, a temperature change of 0.01°C will not cause the optimal level of the tourism climate to shift to other categories of the TCI. However, it is the cross-cultural differences of the tourists and their climatic preferences that will result in uncertainty, and this is the aspect that previous tourism climate indices had not provided as a practical evaluation consonant with the real condition. Cross-cultural characteristics of tourism climate is a common terminology frequently used in the tourism climate literature to demonstrate different preferences of tourists, who come from different origin climates, toward favorability of climate for tourism activities (see Gómez-Martín 2006, De Freitas et al. 2008, Scott et al. 2008, Rutty & Scott 2015). The results of our empirical study confirm cross-cultural differences of tourism climate, which was reported by more than 200 beach-users in North Cyprus. Hence, the first step is to show statistically significant cross-cultural differences in tourism climate and the second phase is to address the complexity of tourism climate, which is enhanced by the aforementioned differences, through a mathematical and computerized method (fuzzy logic in MATLAB software).

In this study, inputs of the fuzzy system are the variables of CIT that are considered, namely, thermal sensation, cloud cover, wind, and rain, and output is the climate satisfaction rating that ranges from Very Poor (1 = unacceptable) to Ideal (7 = optimal). Inputs and fuzzy rules are defined according to surveyed tourists' preferences regarding optimal weather conditions . The fuzzy inference engine acts based on the fuzzy rule, which is extracted from existing knowledge about the tourism climate.

3. MATERIALS AND METHODS

3.1. Samples and procedure

This research was conducted in 2 phases (see Fig. 2 for the research model). First, a survey was conducted to identify the important levels of the tourism climate parameters and the thresholds of the climate variables regarding tourists' perceptions of different climate regions. Furthermore, the discriminate range of input data was linked with the 7 levels of CIT. For this purpose, a survey questionnaire was administered, and demographic information, including gender, age, nationality, and origin climate of the respondents, were included in the administered questionnaire.

The sample contained 203 tourists who were vacationing on the Mediterranean beaches of Famagusta, North Cyprus, for the duration of 2 wk in May 2013. There are 2 reasons for selecting beach-users to test the proposed model: (1) 3S tourism is the most popular tourism activity in the study area, and (2) the last attempt at modeling the CIT (De Freitas et al. 2008) targeted seaside holidaymakers. As our model built on their study, it is rationally justifiable to focus on this segment of tourism. The multicultural characteristics of the tourists were important; therefore, the targeted respondents were from 12 countries with cultural and climatic variations. For this purpose, the convenient/non-probability sampling technique was used. To ensure the clarity of the questionnaire, a pilot study was developed and pre-checked on 20 respondents. The designed questionnaire was appropriate and clear to the respondents (Podsakoff et al. 2003). The questionnaire focused on extracting the logic of respondents regarding their climate preferences while they actively or passively spend time on the beach.

The demographic information related to the tourists who were interviewed is summarized in Table 1.

In the second phase, methodological parameters as input data and tourism/climate as output data were divided into a number of categories with Gaussian membership functions (MFs). There are c^n fuzzy rules, where n refers to the number of subsets and c to the number of input factors. Fuzzy system efficiency is boosted when the number of subsets increases, but the larger rule base is more difficult to construct (Sen 1998). In the case of 1 input, x (thermal sensation) with k subsets, the rule base takes the form of an output y_n (CIT). If there is 1 input variable such as x with 'Cold,' 'Neutral,' and 'Hot' fuzzy subsets, there will consequently be 3 'IF–THEN' rules as follows:

Rule 1: IF x is Cold, THEN y_1.

Rule 2: IF x is Neutral, THEN y_2.

Rule 3: IF x is Hot, THEN y_3.

w_n, membership degree, for x is computed to be assigned to the corresponding output y_n for each rule triggered. Thus, the weighted average of the outputs from the 3 rules results in a single weighted output 'y' as:

$$y = \frac{\sum_{n=1}^{3} w_n \cdot y_n}{\sum_{n=1}^{3} w_n} \quad (2)$$

Thus, the values of the output y can be computed from Eq. (2) for any combination of input parameter fuzzy subsets after setting up the rule base. Deriving the necessary rule base by the fuzzy inference procedure using sample data is a very common method used to make decisions about the fuzzy rule base (Sen 1998).

After compiling field data in the first phase, MATLAB software was applied to formulate the tourism climate through fuzzy sets in the second phase (see Fig. 2), which is elaborated in the following section.

Table 1. Demographic information for tourists vacationing on the Mediterranean beaches of Famagusta, North Cyprus, for 2 wk in May 2013. Respondents were interviewed to determine important levels of the tourism climate parameters. Origin was defined based on climatic types adapted from global climate descriptions of Meehl et al. (2007)

Variable	Frequency	Percent
Gender		
Male	142	69.9
Female	61	30.1
Total	203	100
Age (yr)		
18–27	89	43.7
28–37	89	43.7
38–47	12	5.8
58–67	14	6.8
Total	203	100
Origin of the respondents		
Tropical (Cameroon, Ghana, Nigeria)	41	20.4
Dry (Azerbaijan, Iran, Kazakhstan, Tajikistan)	71	35
Moderate (England, Israel, Romania, Turkey)	79	38.8
Continental (Russia)	12	5.8
Total	203	100

3.2. Data analyses

The first stage of the survey focused on the perceived importance of specific facets of 3S tourism with respect to climate. To check the cross-cultural differences of the tourism–climate nexus, Tukey's test was employed to explore the preferences of tourists from 4 climate regions (tropical, dry, moderate, and continental). In addition, the Friedman test was used to demonstrate the rank of importance of the climate variables from the tourists' point of view with respect to their cultural differences (Friedman 1940).

The second phase of the survey analysis set out to identify the optimal conditions for beach tourism. The thermal (T), aesthetic (A), and physical (P) facets were combined in a holiday weather typology matrix of ratings from 1 (worst) to 7 (optimum). Median and mean responses from the survey questionnaire were used to identify the central tendencies and to complete the matrix, which covered every combination of T, A, and P (De Freitas et al. 2008). The minimum/maximum of each variable that has a reasonable frequency was used in the rating system of fuzzification to cover the preferences of the majority of the respondents with various origin climates. Therefore, the results of mean and the maximum/minimum of the climate variables (ranges) created the knowledge that was used within the fuzzy inference engine in the second phase of the study (see Fig. 2). The matrix typology of the 3 facets in the context of 4 inputs was analyzed using MATLAB, which is a numerical computation of the climate environment.

The next step was the defuzzification of the model and its subsequent export to function as software that inserts input variables. Fuzzy-based CIT was calculated at different time scales ranging from hourly to yearly data. The existing knowledge that was obtained based on the tourist preferences and their linguistic expressions was then translated by computer. Thus, the process of estimation was accelerated effectively and precisely.

4. RESULTS

Statistical analysis of the field data, including the Tukey and Friedman tests, was conducted to prove the cross-cultural differences in climate preferences of tourists involved in leisure activities on the beach.

4.1. Cross-cultural differences of CIT

As elaborated earlier, Tukey's test was employed to explore the climate preferences of tourists from 4 climate regions (tropical, dry, moderate, and continental). An analysis comparing the mean differences of perception of the climate facets among tourists from different cultures is shown in Table 2.

The results show that tourists who come from continental and tropical climate regions have significantly different preferences in terms of thermal sensation at the beach (mean difference = 1.6, $p < 0.01$). Tourists from regions with a moderate climate have a different optimal perception about sunshine compared to tourists from tropical (mean difference = 0.89, $p < 0.01$) and dry climate regions (mean difference = 0.98, $p < 0.001$). Cloudiness is another climate facet that beach goers from a dry climate reported as a significant difference from tropical (mean difference = 1.33, $p < 0.001$) and moderate climate regions (mean difference = 1.6, $p < 0.001$).

The comparisons of the means of the physical facets of the climate, including wind and rain, were not considered because there were no significant differences among tourists' perception, notwithstanding origin climate variations. However, in general, cross-cultural climate preferences in relation to beach users are supported, and tourists from

Table 2. Comparing means of climate facets based on tourists' perspectives in relation to climatic variation in different regions; $^{*}p < 0.01$, $^{**}p < 0.001$

Climate variable Origin climate of the tourists		Mean difference	p
Thermal sensation			
Tropical	Dry	−0.65	0.16
	Moderate	−0.46	0.42
	Continental	−1.60*	0.01
Dry	Tropical	0.65	0.16
	Moderate	0.19	0.88
	Continental	−0.94	0.23
Moderate	Tropical	0.46	0.42
	Dry	−0.19	0.88
	Continental	−1.13	0.10
Continental	Tropical	1.60*	0.01
	Dry	0.94	0.23
	Moderate	1.13	0.10
Cloud cover			
Tropical	Dry	1.33*	0.005
	Moderate	−0.28	0.884
	Continental	0.71	0.693
Dry	Tropical	−1.33*	0.005
	Moderate	−1.60**	0.000
	Continental	−0.61	0.759
Moderate	Tropical	0.28	0.884
	Dry	1.60**	0.000
	Continental	0.99	0.378
Continental	Tropical	−0.71	0.693
	Dry	0.61	0.759
	Moderate	−0.99	0.378
Rain			
Tropical	Dry	−0.44	0.680
	Moderate	0.28	0.883
	Continental	−0.19	0.992
Dry	Tropical	0.44	0.680
	Moderate	0.73	0.131
	Continental	0.25	0.979
Moderate	Tropical	−0.28	0.883
	Dry	−0.73	0.131
	Continental	−0.48	0.874
Continental	Tropical	0.19	0.992
	Dry	−0.25	0.979
	Moderate	0.48	0.874
Sunshine			
Tropical	Dry	0.09	0.99
	Moderate	−0.89*	0.03
	Continental	−0.88	0.38
Dry	Tropical	−0.09	0.99
	Moderate	−0.98*	0.003
	Continental	−0.97	0.25
Moderate	Tropical	0.89*	0.03
	Dry	0.98*	0.003
	Continental	0.01	1.00
Continental	Tropical	0.88	0.38
	Dry	0.97	0.25
	Moderate	−0.01	1.00
Wind			
Tropical	Dry	0.92	0.07
	Moderate	0.16	0.97
	Continental	0.12	1.00
Dry	Tropical	−0.92	0.07
	Moderate	−0.76	0.08
	Continental	−0.81	0.54
Moderate	Tropical	−0.16	0.97
	Dry	0.76	0.08
	Continental	−0.04	1.00
Continental	Tropical	−0.12	1.00
	Dry	0.81	0.54
	Moderate	0.04	1.00

Table 3. Results of the Friedman test used to demonstrate the rank of importance of climate variables from tourists' point of view. $\chi^2 = 38.7$ ($p < 0.01$)

Variables	Mean	SD	Mean rank
Absence of rain	5.9	1.4	2.9
Comfortable thermal sensation	5.7	1.2	2.6
Sunshine	5.7	1.3	2.5
Absence of strong wind	4.9	1.4	1.9

various climates reported different preferences for thermal sensation, cloud cover, and sunshine parameters.

In addition, the Friedman test was used to demonstrate the rank of importance of climate variables from the point of view of tourists from different cultures (Table 3). The results indicate that tourists reported different priorities for climate facets. From a tourism point of view, especially in the case of beach activities, the climatic variations of different beaches have a significant implication for attracting different tourists with respect to their origin climate.

The results of the Friedman analysis proved that 203 tourists from various origin climates (tropical, dry, moderate, and continental) declared different preferences in relation to 4 climate parameters ($\chi^2 = 38.7$, $p < 0.001$, Table 3).

4.2. Fuzzy logic

The results of the 3 processes of fuzzy logic application in the calculation of CIT are presented as follows:

4.2.1. Fuzzification

In the fuzzification stage, the fuzzy controller accepts the crisp inputs (i.e. thermal sensation, wind, cloudiness, and precipitation) and maps them into their MFs, known as fuzzy sets. Fuzzification determines the degree of membership for a crisp input x being applied to appropriate fuzzy set μ. The degree of membership is a number between 0 and 1:

$$\mu: x \quad [0,1] \tag{3}$$

A value of 0 means that x is not a member of the fuzzy set, whereas a value of 1 means that x is a full member of the fuzzy set. The values between 0 and 1 characterize fuzzy members that partially belong to the fuzzy set. An MF is a curve that defines how each

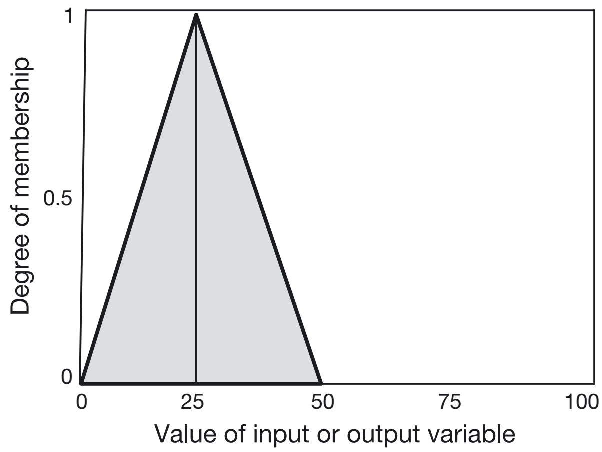


Fig. 3. Example of a triangular membership function

point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse (Jang 1997). The most commonly used shapes for MFs are triangular, trapezoidal, and Gaussian. Among them, the triangular MF is the simplest and most frequently used (Pedrycz 1994, Jang 1997). In the proposed fuzzy-based CIT, the MFs assigned to input and output variables are chosen to be triangular. The triangular edges can be identified by the points (a, b, c) (with a < b < c). The parameters (a, b, c) determine the x coordinates of the 3 corners of the underlying triangular function. Fig. 3 illustrates a triangular MF defined by the triangle (0, 25, and 50). The point 25 has the largest value in the MF.

We defined fuzzy MFs for thermal sensation, cloudiness, wind, and precipitation as the input metrics and fuzzy-based CIT as the output parameter as follows.

Three to 7 curves are generally appropriate to cover the required range of an input value or the universe of discourse in a fuzzy region. We examined the fuzzy system using 5 and 7 curves (Table 4).

As depicted in Fig. 4, the states of the input variable no longer change abruptly from one state to the next. Instead, as the input changes, it loses a value in one MF while gaining a value in the next. In other words, an input variable is, to some degree, part of 2 MFs. In Fig. 4a, for example, when the temperature is 24°C, the input fully belongs to the MF Cool (CL). However, when the temperature is 25.5°C, the input is partially (0.5 each) part of 2 MFs — CL and Slightly Cool (SC). As Ebrahimi et al. (2013) indicated, a fuzzy system is constructed based on human expertise and expert knowledge.

Table 4. Type, curve number, and universe of discourse ranges of variables. Wind was classified based on the Beaufort Scale. Membership functions are illustrated in Fig. 4. CIT: Climate Index for Tourism

Variable	Number of curves	Curve 1	Curve 2	Curve 3	Curve 4	Curve 5	Curve 6	Curve 7
Input								
Thermal sensation (°C)	7	Cold (CD) [20, 23]	Cool (CL) [20, 24, 27]	Slightly Cool (SC) [24, 27, 29]	Neutral (N) [27, 29, 31]	Slightly Warm (SW) [29, 31, 34]	Warm (W) [31, 34, 38]	Hot (H) [34, 38]
Wind speed (km h^{-1})	7	Calm (C) [0, 3]	Light Air (LA) [0, 3, 9]	Light Breeze (LB) [3, 9, 16]	Gentle Breeze (GB) [9, 16, 24]	Moderate Breeze (MB) [16, 24, 34]	Fresh Breeze (FB) [24, 34, 44]	Strong Gale (SG) [34, 44]
Precipitation (mm h^{-1})	7	No Rain (N) [0, 0.2]	Very Low (VL) [0, 0.2, 0.7]	Low (L) [0.2, 0.7, 1.2]	Medium (M) [0.7, 1.2,1.7]	Slightly High (SH) [1.2, 1.7, 2.2]	High (H) [1.7, 2.2, 2.5]	Very High (VH) [2.2, 2.5]
Cloudiness (%)	5	Clear (C) [0, 25]	Lightly Cloudy (LC) [0, 25, 50]	Partly Cloudy (PC) [25, 50, 75]	Cloudy (CL) [50, 75, 100]	Overcast (OC) [75, 100]	–	–
Output								
Fuzzy-based CIT	7	Very Poor (VP) [1, 2]	Poor (P) [1, 2, 3]	Unfavorable (U) [2, 3, 4]	Marginal (M) [3, 4, 5]	Good (G) [4, 5, 6]	Very Good (VG) [5, 6, 7]	Ideal (Id) [6, 7]

4.2.2. Fuzzy inference system

An inference engine is equipped with fuzzy rules to make a decision for an output index based on the current condition of the weather. The inference engine is characterized by a set of linguistic statements that describe the system using a number of conditional 'IF–THEN' rules: The 'IF' part is called the 'antecedent' and the 'THEN' part is called the 'consequent.' Expert knowledge is usually used to form the rules of a fuzzy inference system. In our study, knowledge was extracted from the experience and expressions of 203 tourists who came from different climates.

Fuzzy rule sets usually have several antecedents that are combined using fuzzy operators, such as fuzzy intersection ('AND') and fuzzy union ('OR'). If the rule uses an AND relationship for the mapping of 4 input variables, the minimum of those values is used as the output, whereas for the OR relationship, the maximum is used. In fuzzy-based CIT, the AND operator is utilized to combine the fuzzy inputs.

To explain the fuzzy inference and defuzzification process in a simple way, consider 2 input variables (temperature and cloudiness) as an example in Fig. 5, in which temperature and cloudiness have the values of 32°C and 20%, respectively. As shown in Fig. 5a, a temperature of 32°C is a part of the MFs Slightly Warm (SW) and Warm (W), and the portion of each MF is 0.5. A cloudiness value of 20% is a part of the MFs Clear (C) and Lightly Cloudy (LC), as illustrated in Fig. 5b. In this case, the degree of membership for MFs C and LC is 0.2 and 0.8, respectively.

Considering these 2 input variables, there are 4 combinations between temperature and cloudiness:
(1) Temperature: SW and Cloudiness: C
(2) Temperature: SW and Cloudiness: LC
(3) Temperature: W and Cloudiness: C
(4) Temperature: W and Cloudiness: LC

Based on these combinations, the following 4 rules are depicted in Fig. 6:

– Rule 1 (Fig. 6a): IF (Temperature is SW) AND (Cloudiness is C) THEN (CIT is Ideal [Id])
– Rule 2 (Fig. 6b): IF (Temperature is SW) AND (Cloudiness is LC) THEN (CIT is Very Good [VG])
– Rule 3 (Fig. 6c): IF (Temperature is W) AND (Cloudiness is C) THEN (CIT is VG)
– Rule 4 (Fig. 6d): IF (Temperature is W) AND (Cloudiness is LC) THEN (CIT is Good [G])

4.2.3. Composition and defuzzification

Defuzzification is the process of producing a quantifiable result in fuzzy logic and converting the fuzzy control action into a crisp value. The outputs of all rules should be aggregated and converted into a single output. The center-of-gravity approach (CoG) has been used as a defuzzification method to produce a crisp value. This method finds the geometrical center (Ebrahimi et al. 2013) and favors the rule with the output of the greatest area.

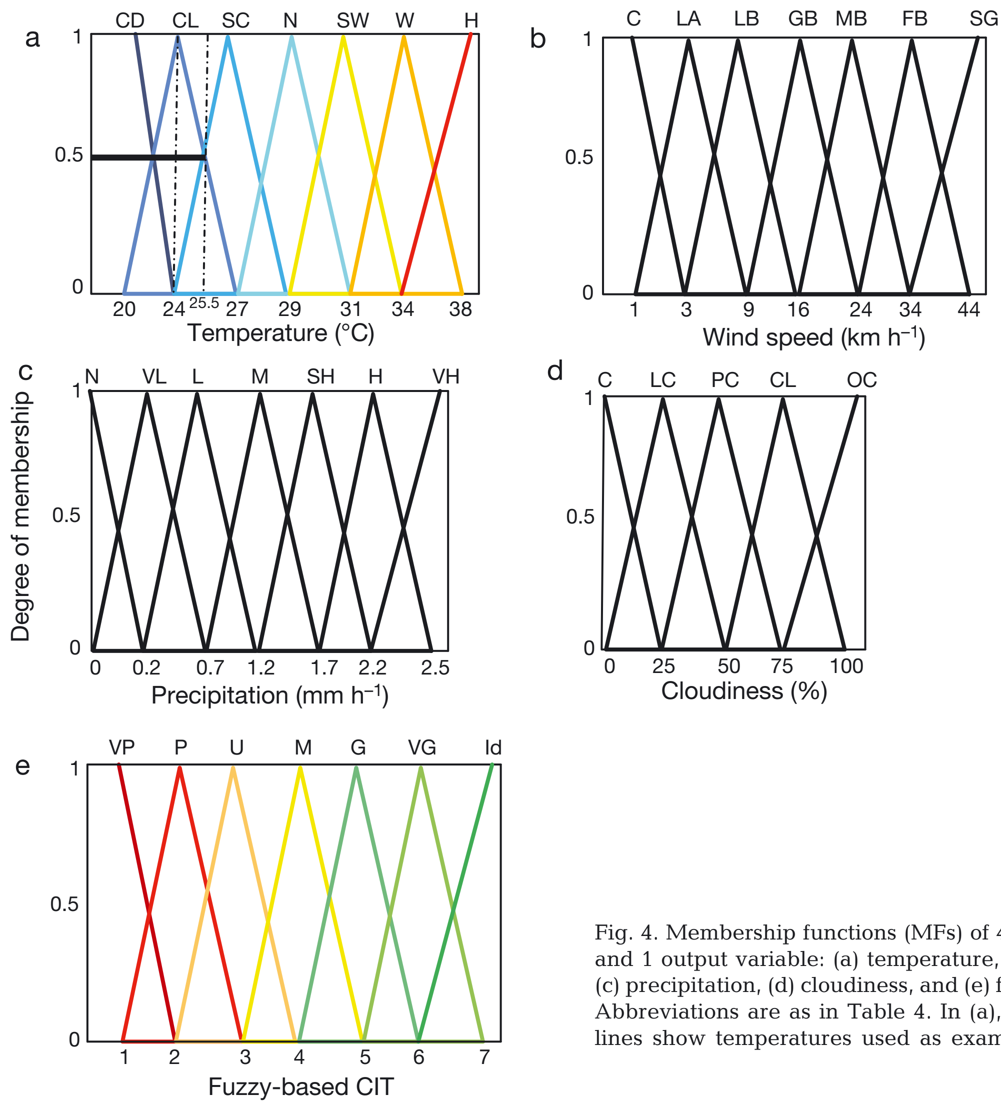


Fig. 4. Membership functions (MFs) of 4 input variables and 1 output variable: (a) temperature, (b) wind speed, (c) precipitation, (d) cloudiness, and (e) fuzzy-based CIT. Abbreviations are as in Table 4. In (a), vertical dashed lines show temperatures used as examples in the text

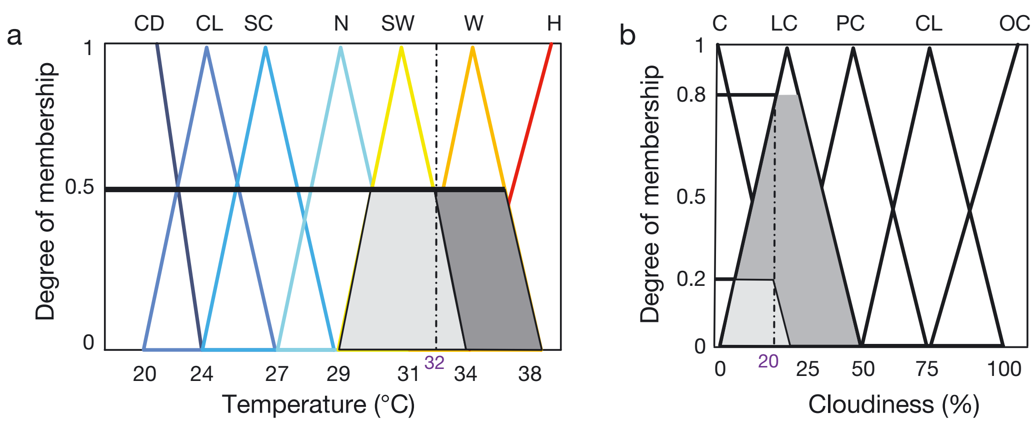


Fig. 5. (a) Temperature and (b) cloudiness as a part of 2 membership functions (MFs). Abbreviations are as in Table 4

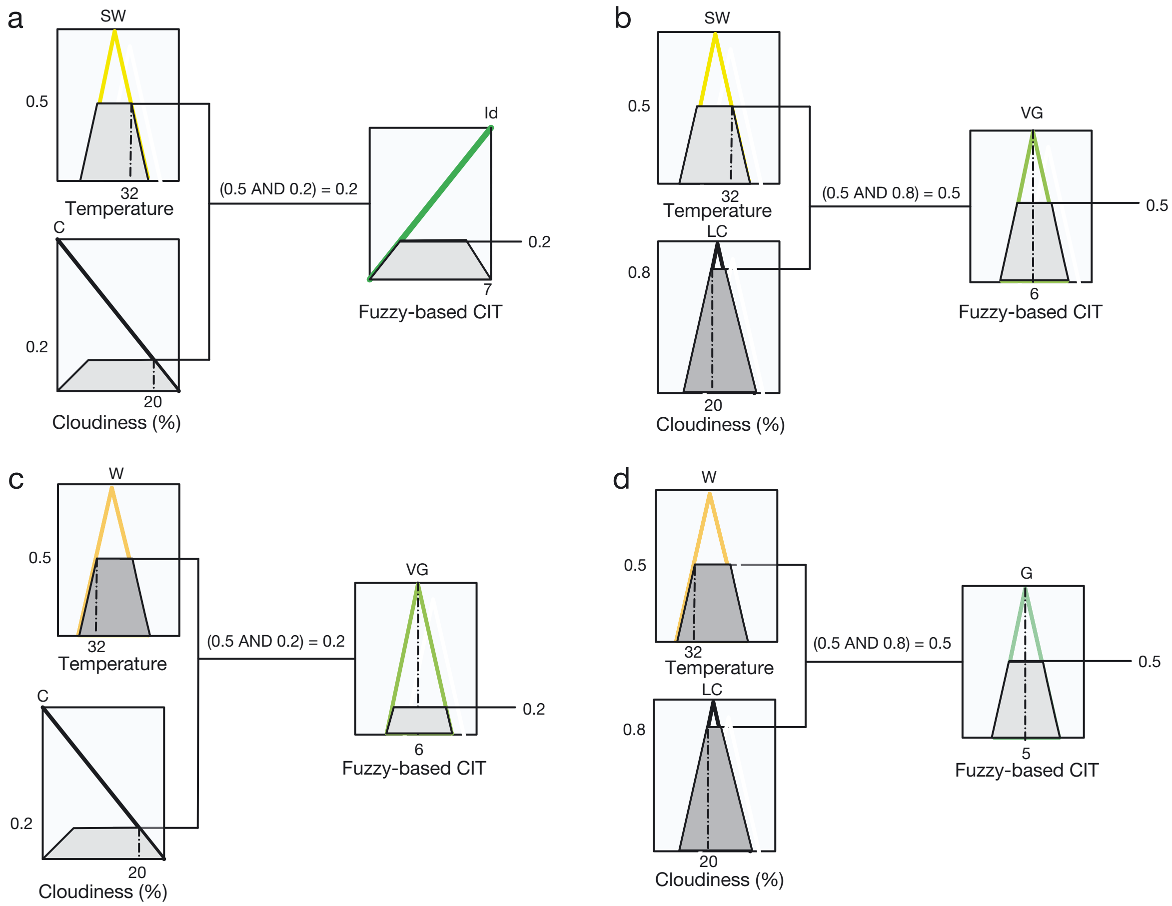


Fig. 6. Fuzzy-based Climate Index for Tourism (CIT) for (a) Rule 1, (b) Rule 2, (c) Rule 3, and (d) Rule 4. See Section 4.2.2. for detailed descriptions of these rules. Abbreviations are as in Table 4; shading scheme follows Fig. 5

In the defuzzification stage, the 4 obtained fuzzy-based CIT values (Fig. 6) are combined, and by using the CoG method, a single fuzzy-based CIT value is extracted. As shown in Fig. 7, the fuzzy outputs of the same fuzzy-based CIT MF are summed, while the values in different MFs are united (i.e. the maximum value is considered). In this case, the fuzzy-based CIT value can be calculated from the following formula:

$$\text{Obtained Fuzzy-based CIT} = \frac{\textit{Obtained CIT}}{\textit{Degree of membership functions}} \quad (4)$$

$$= \frac{(7\times 0.2)+(6\times 0.5)+(6\times 0.2)+(5\times 0.5)}{0.2+0.5+0.2+0.5} = 5.78$$

According to this formula, the degree of MF of each rule is multiplied by the fuzzy-based CIT value associated with the maximum value in the MF and then divided by the sum of all the degrees of MFs. The obtained fuzzy-based CIT value in this example is about 6, which is 'Very Good' weather for beach goers.

The results of the fuzzy logic analysis using MATLAB software are provided in Fig. S1, available in the Supplement at www.int-res.com/articles/suppl/c066p049_supp.pdf. According to Kiszka et al. (1985), after adding climate parameters as input data (Fig. S1a) and fuzzy-based CIT as output (Fig. S1b), the MFs for each variable were designated. A fuzzy rule base was also used in the current study, which can be achieved step by step from sets of input and output data (Fig. S1c). The membership value (w_n) for x in each of the fuzzy subsets was computed, and output y_n was obtained considering the complete set of rule weights w_n. Finally, the weighted average similar to Eq. (2) was calculated (Fig. S1c).

The proposed approach has sufficient flexibility to enable the addition of other variables (e.g. seawater temperature, origin of tourists, age, gender, etc.) as inputs into the system. Thus, fuzzy logic can be applied as a useful tool to overcome complexity and the uncertainty of climate well-being for tourists with different profiles.

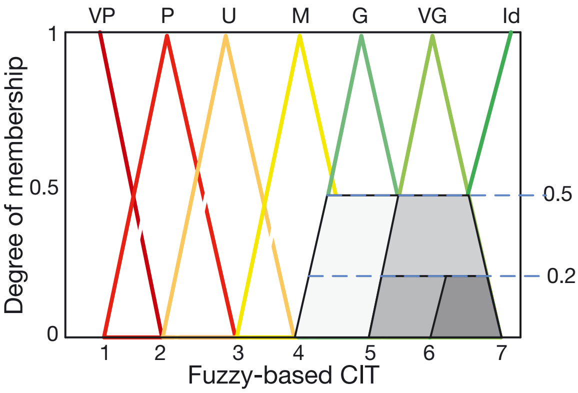


Fig. 7. Composition of the fuzzy-based Climate Index for Tourism (CIT) membership function (MF) of all rules and producing a crisp value using the center-of-gravity (CoG) method. Abbreviations are as in Table 4

4.3. Support of overriding effect

The fuzzy toolbox of MATLAB software has the convenient flexibility to allow users to set rules based on human logic. When the rules were defined, the overriding effects of wind and rain were considered as follows:

- IF (Wind is Fresh Breeze) THEN (CIT is Very Poor [VP])
- IF (Precipitation is High [>2.5 mm h^{-1}]) THEN (CIT is VP)

The rule editor of MATLAB is shown in Fig. S1c.

4.4. Comparison of fuzzy-based CIT and CIT

To identify the differences between fuzzy-based CIT and CIT, the assumptions and findings of our research are compared with those of De Freitas et al. (2008).

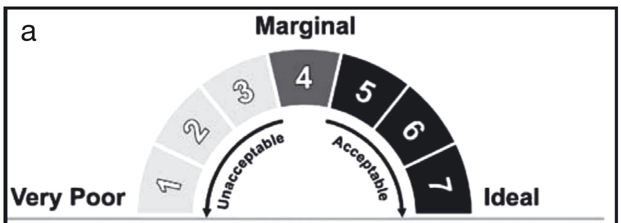
If the thermal sensation is Slightly Warm, the percentage of cloudiness is <50 %, rain is 0, and wind is 0, then CIT is 6. Therefore, the output is the same; however, when differences between the proposed approach (fuzzy-based CIT) and the CIT arise, as elaborated above, FLS can address the drawbacks of CIT as follows.

4.4.1. Computing with words

With the exception of thermal sensation, CIT cannot support word computing. In other words, we cannot use linguistic expressions (e.g. 'Lightly Cloudy' or 'Light Breeze') in the calculation process of the climate tourism index. In addition, the interpretation of the output of CIT (Fig. 8) is not a straightforward task for amateur users. The FLS function is a tool that requires input variables to be entered into the system and output to be calculated quickly with an acceptable level of accuracy. Furthermore, FLS has the flexibility to consider more input variables, whereas adding more variables for the calculation and interpretation of the CIT requires high levels of skill. As shown in Fig. S1, cloudiness <50 % or rain <3 mm h^{-1}, as well as a more precise range of wind speed, was ignored. In addition, a mathematical method (CoG) was employed in the calculation of output, whereas in CIT, output is estimated based on a subjective approach.

4.4.2. Addressing the multicultural aspect of CIT

Fuzzy-based CIT considers a range for each specific expression, while CIT regards a point as a boundary between 2 levels (binary method). As a tangible example, in the binary system, 32°C is considered slightly warm weather, and it cannot be considered both 'Slightly Warm' and 'Warm' simultaneously, even though, for example, 32°C may be considered 'Slightly Warm' by an African tourist and 'Warm' by a Russian tourist. Meanwhile, FLS empowers us to consider 32°C as 'Slightly Warm' and 'Warm' with different MFs at the same time (Fig. 5a).



b ASHRAE scale TSN [T]		Cloud (≤40%) [A]	Cloud (≥50%) [A]	Rain (>3mm or >1hr duration) [P]	Wind (≥6m/s at ground) [P]
Very hot	(+4)	4	3	2	3
Hot	(+3)	6	5	2	4
Warm	(+2)	7	5	2	4
Slightly warm	(+1)	6	4	1	4
Indifferent	(0)	5	3	1	2
Slightly cool	(-1)	4	3	1	2
Cool	(-2)				
Cold	(-3)				
Very cold	(-4)				

Fig. 8. Climate Index for Tourism (CIT) ratings based on thermal conditions (T), expressed as thermal sensation (TSN) on the ASHRAE scale; aesthetic quality (A); and physical factors (P). Source: De Freitas et al. (2008)

To further clarify this issue, in the context of CIT, 20% is considered equal to 0, 10, 30, and 39% of cloudiness. However, a British tourist, for example, might perceive this level of cloudiness as a 'Clear' sky, whereas for a Middle Eastern tourist this may be considered 'Lightly Cloudy.' Nevertheless, FLS is able to solve this issue by using different MFs. In other words, 20% cloudiness is perceived as 20% 'Clear' sky, and/or 80% 'Lightly Cloudy' (Fig. 5b). Thus, whereas in previous indices, multicultural differences in the tourism climate were ignored, these differences can be addressed by fuzzy-based CIT.

Furthermore, a tourist's cultural identity in association with his/her home climate can be considered as an input variable (i.e. using the adaptive neuro-fuzzy inference system [ANFIS] approach), which we propose as an implication for future research.

4.4.3. From theory to practice

To calculate a CIT with 4 input variables and 1 output variable on 7 levels, more than 1200 rules must be considered. Hence, in the previous approach, various assumptions were employed to simplify the estimation and interpretation of the output of CIT. As illustrated in Fig. 8, there are no differences between 40% and 5% cloudiness and wind with 1 m s^{-1} (3.6 km h^{-1}) and 5.9 m s^{-1} (21 km h^{-1}). If we add the drawback of the lack of supporting linguistic expressions to the problem of the uncertain range of input variables in CIT as well as the sophisticated process of output interpretation, we discover why this approach is not used by practitioners, such as tour operators, planners, and insurance agents. Conversely, to calculate fuzzy-based CIT, the user should enter 4 input variables, and output will be calculated precisely (considering all effective dimensions and all possible values) and quickly (the computer assists in the calculation process by considering numerous rules that are extracted from human linguistic knowledge and the experiences of beach goers).

5. DISCUSSION AND CONCLUSION

Weather and climate are crucial resources for tourism activities. This empirical study proposes a computer-based method to provide more accurate assessment regarding climate suitability of touristic destinations that vary by spatial and temporal changes in climate, as well as by spatial patterns of tourist flows (cross-cultural characteristics of tourism climate). Our empirical study not only statistically supports cross-cultural differences in properties of the tourism–climate nexus, it also applies fuzzy logic to address 2 main complex issues of tourism climate, namely (1) expression of tourist preferences toward climate well-being in linguistic terms that can be translated, using fuzzy logic, into numerical values that are readable by computer, and (2) cross-cultural characteristics of the tourism–climate nexus addressed by utilization of fuzzy thresholds for weather facets. The latter section is required for implementation of cross-cultural differences in the determination of weather preferences. It is common to use a computer-based index that covers various ranges of tourists' preferences. In the meantime, extending the use and appeal of the tourism climate index will assist planners to manage tourism activities through evaluation of weather/climate effects on tourism demand. This will have useful implications for decision making in terms of climate variability, services that are climate dependent, destination promotion, and development of climate information logs for tourists and businesses.

Actual and potential changes in suitability of climate for tourism have been subjected to considerable scientific research, resulting in more refined and sophisticated representations of climatic conditions — for example, in terms of their empirical foundation and the consideration of cross-cultural differences. In accordance with studies by Gómez-Martín, (2006), De Freitas et al. (2008), and Rutty & Scott (2015), our empirical research has supported cross-cultural differences in properties of the tourism–climate nexus. Importantly, the uncertainty that surrounds the nature of both climate facets and the complexity of the cross-cultural preferences of tourists is addressed using FLS. Thus, this study has contributed to the tourism climate literature through the application of fuzzy logic, which can translate human linguistic knowledge into computer language.

The lessons from fuzzy logic have proven that identifying a certain threshold for variables and establishing a tourism climate model according to the statistical analysis of natural facets, such as temperature, visibility, and so on, are not strongly validated. Specifically, tourism demand and perception vary from culture to culture. For instance, a very hot temperature has a different meaning for a Russian tourist than it does for an African tourist. Accordingly, the results of the statistical analysis showed that the tourists reported different preferences for climate facets — that is, tourists from regions with tropical, dry, moderate, and continental climates have different perceptions of thermal sensation, sunshine, and cloudiness. Such evidence is consonant with the results of De Freitas et al. (2008) and Morgan et al. (2000). Hence, fuzzy logic helps to address the complexity of the tourism climate issue. In addition, fuzzy logic assists in the interpretation process of natural events whose key characteristics are uncertainty and randomness.

Previous indices could not cover cross-cultured facets of tourism climate. In contrast, fuzzy logic expresses a specific level of a climate parameter for a certain category, while simultaneously it can be considered in another category of that variable. It accounts for the tourism–climate nexus through a special weight and rules. For instance, 32.5°C can convey a sense of 'Slightly Warm' with a weight of 0.7, whereas it may be considered a 'Warm' sensation with a weight of 0.3. Therefore, when we decide to make a decision regarding different tourists' preferences based on various natural parameters, the applicability level of this logic emerges. As previously elaborated, fuzzy logic can address the problem of uncertainty regarding natural elements and the potential effects of climate change on ecosystem resilience and ecological integrity (Prato 2010). Kişi & Tombul (2013) provided a precise estimation for natural elements, such as monthly evaporation and other climate indices, using fuzzy sets.

The fuzzy rules system assists with the input of different variables and dates that can be interpreted and analyzed based on human linguistic knowledge. This means that different climate variables can be entered into the system and can interpret the linguistic knowledge to determine the level of climate favorability with diverse activities spatially and temporally. Finally, applying IF–THEN rules with an overriding effect is automatically controlled via computer, because there is a rule that if the precipitation is prolonged by more than 2.5 mm h^{-1} and accompanied by a slight breeze, then the climate is unfavorable (De Freitas et al. 2008). This is consonant with the results of Zadeh (2008) and Novák (2006), who noted that fuzzy logic acts as a powerful modeling language in uncertain systems through the formalism of linguistic variables and fuzzy IF–THEN rules.

5.1. Implications

A technical setting is provided for the estimation of the tourism climate through computer software that can facilitate the prediction of climate congruence with tourist satisfaction for planning by tour operators, insurance companies, and tourism planners and managers. Furthermore, notwithstanding the growing interest in climate change, the tourism–climate nexus has not received deserved attention regarding the development of a practical model. In fact, there has been stagnation in regard to this topic (Kaján & Saarinen 2013). However, with the growing concern and scientific discourses about climate, the tourism industry circles on both sides of the sector (i.e. destinations and markets) are realizing that some policy changes need to be contemplated (Gómez-Martín 2006).

Our study aimed to facilitate this process by focusing on building a practical model geared toward the (re)distribution of tourists to beach resorts where the climatic conditions are conducive to their comfort zone with respect to the optimum climate. The optimum climate is characterized based on the CIT, and is a pleasant climatic condition pertinent to the tourist's origin climate. This is possible by identifying/defining different beach resorts (i.e. branch-specific) in different geographic regions of the destination in terms of CIT (Trawöger 2014). One should keep in mind that the profiles of the beach, the coast, and the sea are determined by the climatic characteristics of the destination (Burton 1995). For instance, Mediterranean climatic characteristics (i.e. average temperature, amount of precipitation, and percent humidity as the main climatic factors) provide a suitable condition for beach formation and calmness of the sea. This study provides a practical approach to tourism management, especially in regard to 3S tourism in 2 ways. Firstly, fuzzy logic allows us to convert linguistic terms to numerical values with readability format for computers. This is very helpful because tourism climate is a complex matter. Furthermore, attractiveness of the climate for tourists depends on several factors and rules, which can be accelerated by computer. Secondly, fuzzy logic does not work based on a binary system. In other words, cross-cultural properties of tourism climate cannot be precisely set on a special threshold (value) for a particular zone. Therefore, fuzzy logic is a practical approach that tackles this problem by considering a wider range of preferences regarding to climatic parameters. Consequently, it covers a wide range of tourists' perceptions.

Climate is frequently cited as one of the viable resources that have a significant effect on the tourists' process of selecting a destination (Gómez-Martín 2005, De Freitas 2015). To maximize the benefits of a favorable climate for tourism activities, our study provided a practical approach that overcomes the shortcomings of previous indices. The results of this model are not only useful for the spatial (re)distribution of tourists to beach resorts, but it can also be used in other managerial activities such as the development of infrastructure, investment, marketing, etc. Even in the Mediterranean area, the suitability of the climate varies in time and space. Hence, it is wise to manage tourism activities based on an index that covers a wider range of preferences of tourists (cross-cultural issues) and provides more accurate evaluation regarding the climate. Since the proposed method is a computer-based model that can easily change the preference thresholds (i.e. those that are defined based on dominant patterns of tourist flows), the calculation of fuzzy-based CIT can be done easily. In other words, the system can be calibrated quickly and precisely by changing the tourist pattern. By entering the input factors (climatic parameters), the computer can read all of the rules and calculate the suitability of tourism climate. In other words, the proposed model has the convenient flexibility to calculate the favorability level of the tourism climate by changing the tourist pattern (by shifting the threshold of the tourist climate preference) and adding other climate parameters (e.g. seawater temperature) to the software. Furthermore, the proposed approach empowers managers, decision makers, and planners to mitigate the consequences of climate change for the tourism industry by matching the tourist activities to favorable spatial and temporal locations.

5.2. Limitations and directions for future research

The output of this program can be imported via other software, and tourism industry enterprises will be able to accelerate the estimation of climate favorability on an hourly, daily, and monthly scale by entering several effective meteorological parameters. In addition, the integration of fuzzy logic and the neural network or ANFIS has the potential capability to forecast the tourism climate and is thus proposed as a direction for future research. Over time, tourists' preferences change according to the alteration of the tourist pattern in terms of origin and culture. Our research had some limitations, as it focused on only one destination at one time (cross-sectional study). Thus, further research, namely cross-destination analysis with a large sample size across various time periods, is needed to enrich the model, especially the pool of rules. Our model also avoided considering 'polar' and 'desert' as home climates of the respondents in the system, and we recommended inclusion of these facets for further research.

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Editorial responsibility: Nils Chr. Stenseth, Oslo, Norway

Submitted: January 14, 2015; Accepted: July 1, 2015
Proofs received from author(s): September 10, 2015