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Data challenges and solutions in the calculation of Tourism Climate Index (TCI) scores in South Africa

Abstract

Climatic indices are a valuable yardstick for comparing regions of differing climate regimes. This is particularly useful for economic sectors that are heavily climate-reliant. The selection of a vacation destination by tourists is strongly influenced by the climate. Climate influences the choice of destination, the timing of vacations and the success of outdoor attractions. The Tourism Climatic Index (TCI) is a widely adopted measure of the climatic suitability for tourism of a particular destination. The climatic data required for the calculation of climatic suitability using this index, however, provide limitations for its adoption in much of the African continent, for which regular measurement of the complete set of variables does not occur. South Africa is one such example, which although supporting a large network of meteorological stations, has very few recording sunshine hours. This paper therefore proposes a mathematical adaptation of the index to facilitate the calculation of TCI scores for destinations. TCI scores produced using this mathematical adaptation for stations that do have sunshine hour measurements are compared with the scores using the standard TCI equation, and demonstrate suitability of this approach. Such adaptations to the model should facilitate a more widespread use of TCI scores in the global South.

Key words: Tourism Climate Index; climate; tourism; sunshine hours; South Africa

Introduction

Increased competition within the tourism sector, coupled with the potential threats of climate change to tourism, have resulted in the development of an array of methods to quantify the climatic suitability of a destination to tourists, which include a number of tourism climate indices (Fergusson, 1964; Davis, 1968; Murray, 1972; Harlfinger, 1991; Becker, 1998; de Freitas, Scott & McBoyle, 2008). Some of these indices quantify the climatic suitability of a region for particular tourist activities, such as beach and water activities and game viewing (Kovács & Unger, 2014). To facilitate the greatest potential for comparison between tourist destinations, however, indices that quantify the overall suitability of the climate of a location for tourists are necessary (Perch-Nielsen, Amelung & Knutti, 2010). It has been argued that in most instances, a tourists' enjoyment of a destination relies on the combined effects of temperature, wind, rain, amount of sunshine and humidity, which combine to determine both the thermal and aesthetic suitability for tourism (de Freitas, 1990; Gomez-Martin, 2005).

One of the most widely used indices to date is the Tourism Climatic Index (TCI) (Moreno and Amelung, 2009; de Freitas et al., 2008; Kovács and Unger, 2014). This index was initially formulated by

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Mieczkowski (1985) to incorporate the thermal, aesthetic and physical aspects of climatic suitability for tourism (Perch-Nielsen et al., 2010) and to evaluate and quantify the effects of changing meteorological conditions on tourism (Mieczkowski, 1985; Amelung, Nicholls & Viner, 2007). The TCI is scaled according to the level of comfort required for the most common tourist activities, including beach and water activities, game viewing and activities that involve low to moderate levels of physical effort (Amelung & Nicholls, 2014). In addition to the suitability of the index, its continued use in a range of different environments globally (c.f. Scott, McBoyle & Schwartzentruber, 2004; Amelung & Viner, 2006; Amelung et al., 2007; Amelung & Nicholls, 2014; Kovács & Unger, 2014; Fitchett, Grant & Hoogendoorn, 2016) facilitates the comparison of a variety of destinations both regionally and globally on the basis of their climatic suitability.

Mieczkowski's (1985) original TCI formula included twelve climatic variables, each measured at monthly intervals (Scott et al., 2004). However, due to climate data constraints experienced when implementing the index, the number of climate components in the TCI formula was reduced to seven variables which are easily available across Europe (Mieczkowski, 1985; Perch-Nielsen et al., 2010). These seven include monthly means of maximum daily temperature (T_{max}), mean daily temperature (T_{mean}), minimum daily relative humidity (RH_{min}), daily relative humidity (RH_{mean}), precipitation, daily sunshine hours and wind speed (Perch-Nielsen et al., 2010; Amelung & Nicholls, 2014; Rosselló-Nadal, 2014). These seven variables are then combined to form five sub-indices, weighted according to their influence on tourist's well-being (Mieczkowski, 1985; Rosselló-Nadal, 2014). The majority of studies that have used TCIs have made use of the same variables, and the weightings of the sub-indices have largely remained constant (c.f. Perch-Nielsen et al., 2010; Rosselló-Nadal, 2014; Amelung & Nicholls, 2014). Adaptations to the model have been made with the purpose of detecting a greater sensitivity for specific tourist activities (Moreno & Amelung, 2009; Morgan, Gatell, Junyent, Micallef, Özhan & Willams, 2010; Rosselló-Nadal, 2014).

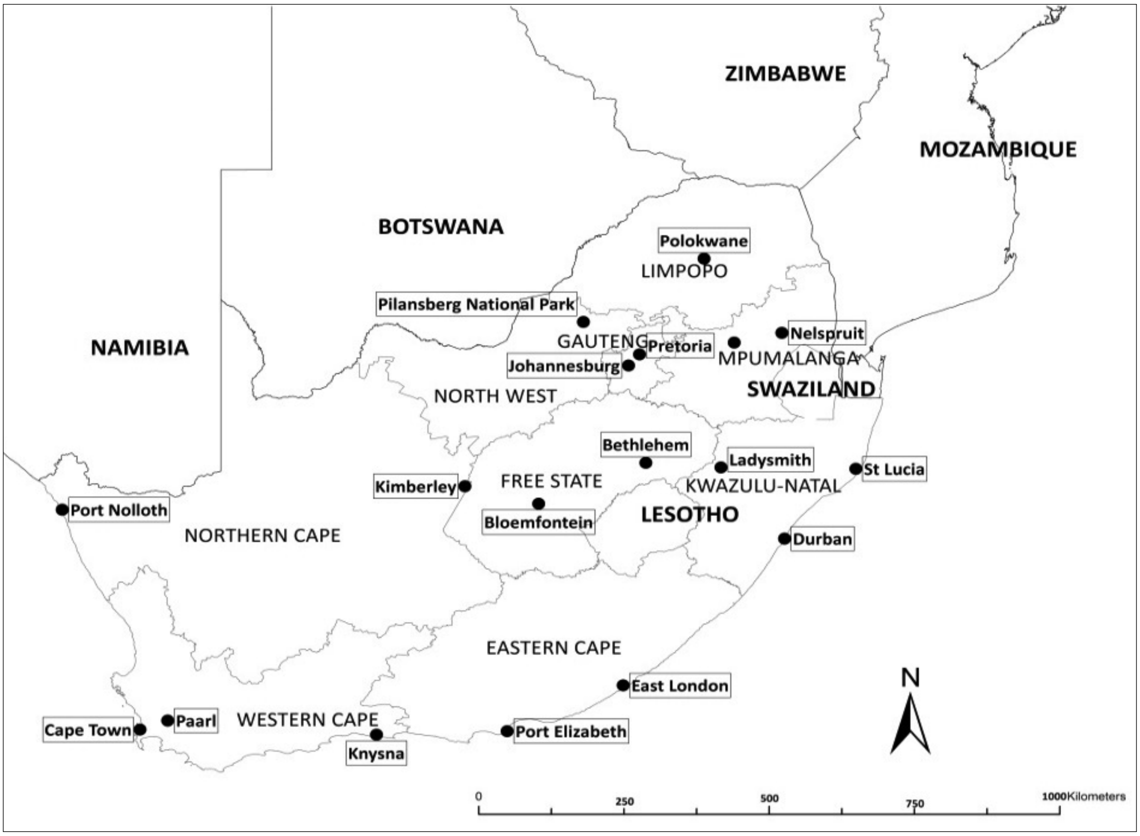
Despite the widespread use of the TCI in the global North, little research has adopted this index in much of the African continent (Hoogendoorn & Fitchett, 2016a, b). This is problematic as it hinders the capacity for the comparison of the suitability of tourist destinations at a global scale (Amelung et al., 2007). For countries such as Botswana and South Africa, tourism sectors are dominated by outdoor attractions, and the climate of the destination is a significant drawcard (Hoogendoorn, Grant & Fitchett, 2016; Hambira, Saarinen, Manwa & Atlhopheng, 2013; Saarinen, Hambira, Athopheng & Manwa, 2012). However, to date, the TCI has been used only once in Southern Africa to quantify the climatic suitability for tourists of two small towns on the South Coast of South Africa: St Francis Bay and Cape St Francis (Fitchett et al., 2016). One of the primary limitations to the use of the TCI in developing countries is the lack of uninterrupted, continuous measurements of each of the component climate variables (Nicholson, Dezfuli & Klotter, 2012; Hoogendoorn & Fitchett, 2016b). Although temperature and precipitation data are available for many locations across Southern Africa, measurements of humidity and sunshine hours are scarcer. By means of a case study, we therefore present two approaches to facilitate the statistically robust calculation of the TCI for locations in South Africa for which sunshine data are not available: the use of rainfall as a proxy, and the mathematical adaptation of the index formula. Despite the success of these approaches, it is argued that the tourism sectors of developing countries would benefit considerably from more comprehensive meteorological recording, and that the potential for calculating accurate indices of climatic suitability for tourism will become critical under climate change in the century to come.

Study region

South Africa is located at co-ordinates 22°-35°S and 17°E-33°E. The country spans the subtropics to the mid-latitudes, with considerable temperature variation from high temperatures reaching in excess of 32°C in summer and several degrees below 0°C at higher elevations on the interior plateau (Jawtusch, 2014). The country is bordered by the warm Agulhas current to the east and the cold Benguela current to the west, inducing an east-west rainfall decrease across the country. South Africa is characterised by winter rainfall conditions in the southwestern region of the country, year-round rainfall along the southern coastline, and summer-rainfall across the central to northern interior (Nicholson, 2000; Chase & Meadows, 2007). Despite these climatic variations, South Africa is considered to have particularly suitable climatic conditions for tourism, and climate forms a significant drawcard to the country.

As part of a broader study on tourism and climate change in Southern Africa, a total of 18 locations were selected, distributed across the nine provinces of the country (Figure 1), and each with a range of tourism attractions (Table 1). These stations were all known to have meteorological stations registered with the South African Weather Services, but the climatic variables available and the data period spanned by these records was unknown during the location selection process.

Figure 1
Map indicating the location of the 18 study sites



Source: Authors.

Table 1
Details of the study sites selected for the study

Location	GPS coordinates	Annual mean temperature (˚C)	Annual mean rainfall (mm)	Tourist attractions
Johannesburg Pretoria	26.2044° S, 28.0456° E 25.7461° S, 28.1881° E	16.0 17.3	543 517	- Business tourism - Arts and cultural tourism - Adventure tourism - Paleo- tourism - Historical tourism
Pilanesberg National Park	25.2611° S, 27.1008° E	19.5	500	- Nature tourism - Adventure tourism - Business tourism - Cultural tourism
Cape Town Paarl Knysna	33.9253° S, 18.4239° E 33.7274° S, 18.9558° E 34.0356° S, 23.0489° E	16.9 17.6 17.0	853 770 779	- Business tourism - Coastal tourism - Adventure tourism - Historical tourism - Arts and cultural tourism - Lifestyle and leisure tourism
Polokwane	23.9000° S, 29.4500° E	17.3	598	- Nature tourism - Adventure tourism - Cultural tourism
St Lucia Durban Ladysmith	28.3833° S, 32.4167° E 29.8833° S, 31.0500° E 29.5597° S, 29.7806 ° E	21.6 20.9 18.3	1129 975 740	- Historical Tourism - Cultural Tourism - Coastal Tourism - Business Tourism
Kimberley Port Nolloth	28.7419° S, 24.7719° E 29.2500° S, 16.8667° E	18.0 14.7	283 72	- Nature tourism - Cultural tourism - Adventure tourism - Historical tourism
Port Elizabeth East London	33.9581° S, 25.6000° E 32.9833° S, 27.8667° E	17.4 18.2	453 593	- Coastal tourism - Nature tourism - Historical tourism - Lifestyle and leisure tourism - Arts and cultural tourism
Bloemfontein Bethlehem	29.1167° S, 26.2167° E 28.2333° S, 28.3000° E	16.1 14.4	407 693	- Adventure tourism - Historical tourism - Cultural tourism - Lifestyle and leisure tourism
Nelspruit Belfast	25.4658° S, 30.9853° E 256833° S, 30.0167° E	19.8 13.2	796 835	- Nature tourism - Lifestyle and leisure tourism - Cultural tourism - Adventure tourism

Methods

The methods used in this paper follow the protocol for reducing the number of climatic variables in the TCI initially used by Mieczowski (1985), and further implemented by Perch-Nielsen et al. (2010). The methods are divided into the acquisition of the climate data, the standard TCI equation, and the mathematical adaptation proposed in this paper.

Data acquisition

Hourly rainfall, minimum temperature, maximum temperature, relative humidity, wind speed were obtained for the 18 study locations from the South African Weather Services. For nine of the locations sunshine hour data were available. Data were obtained for the longest period for which uninterrupted records exist (Table 2); all analyses were performed on both this record and the subset of this data spanning the common period 2005-2014 to facilitate comparability. Data control was performed and ensured by the South African Weather Services.

Table 2
Table indicating the climate data available for the locations used in this study

Location	Max temp	Min temp	Wind speed	Rainfall	Humidity	Sunshine hours
Belfast	2005-2014	2005-2014	2005-2014	2005-2014	2005-2014	
Bethlehem	1981-2014	1981-2014	1981-2014	1981-2014	1981-2014	1981-2014
Bloemfontein	1950-2014	1950-2014	1991-2014	1950-2014	1991-2014	1992-2014
Cape Town	1956-2014	1956-2014	1956-2014	1950-2014	1966-2014	1966-2014
Durban	1957-2014	1956-2014	1956-2014	1956-2014	1956-2014	-
East London	1950-2014	1950-2014	1950-2014	1950-2014	1950-2014	1959-2014
Johannesburg	1985-2014	1985-2014	1992-2014	1985-2014	1992-2014	1992-2014
Kimberley	1950-2014	1950-2014	1950-2014	1950-2014	1950-2014	1959-2014
Knysna	1997-2014	1997-2014	1997-2014	1997-2014	1997-2014	-
Ladysmith	1994-2014	1994-2014	1994-2014	1994-2014	1994-2014	
Nelspruit	1993-2014	1993-2014	1993-2014	1993-2014	1993-2014	-
Paarl	1997-2014	1997-2014	1997-2014	1997-2014	1997-2014	-
Pilanesberg	1996-2014	1996-2014	1996-2014	1996-2014	1996-2014	-
Polokwane	1993-2014	1993-2014	1993-2014	1993-2014	1993-2014	1993-2014
Port Elizabeth	1950-2014	1950-2014	1950-2014	1950-2014	1950-2014	1959-2014
Port Nolloth	1985-2014	1985-2014	1985-2014	1985-2014	1985-2014	1999-2014
Pretoria	1994-2014	1994-2014	1994-2014	1950-2014	1999-2014	-
St Lucia	1983-2014	1983-2014	1983-2014	1983-2014	1983-2014	

Standard TCI

For the nine locations for which all climate data required for the TCI is available, the standard TCI could be calculated. This index developed by Mieczkowsi (1985), and adopted for a range of locations in the global North (cf. Perch-Nielsen et al., 2010; Kovács & Unger, 2014; Kubokawa, Inoue & Satoh, 2014; Roshan, Yousefi & Fitchett, 2016), and is calculated as:

$TCI=2(4CD+CA+2R+2S+W)$

Where:

CD = Daytime thermal comfort

CA = Average thermal comfort

R = Total monthly rainfall

S = Monthly average sunshine hours

W = Monthly average wind speed

Each of the input variables for the model are calculated on the basis of standard climatic data (Table 3). These variables are then rated on a scale with W, R and S spanning a scale from 0 (unfavourable) to 5 (optimal) while CA and CD are scaled from -3 to 5 (Mieczkowski, 1985; Perch-Nielsen et al., 2010; Kovács & Unger, 2014; Roshan et al., 2016). The variables are then assigned a weighting for the model, from which they are summed to a final score with a maximum value of 100 (Perch-Nielsen et al., 2010; Kovács & Unger, 2014).

Table 3
The climate variables component of the TCI model

Sub-index	Abbreviation	Climatic variables required	Weight (%)
Daytime thermal comfort	CD	Mean monthly maximum temperature (˚C) Mean monthly minimum relative humidity (%)	40
Average thermal comfort	CA	Mean monthly temperature (˚C) Mean monthly relative humidity (%)	10
Wind	W	Monthly average wind speed (km/h)	10
Rainfall	R	Total monthly rainfall (mm)	20
Sunshine	S	Daily sunshine (hour)	20

The calculated TCI scores are then classified in terms of the climatic suitability for tourism, ranging from impossible, with scores less than 10, to ideal, for scores greater than 90 (Table 4; Perch-Nielsen et al., 2010). These categories facilitate the comparison of the TCI results from different regions, and if performed consistently, from different studies (Roshan et al., 2016).

Table 4
TCI score rating categories

TCI score	Category
90-100	Ideal
80-89	Excellent
70-79	Very good
60-69	Good
50-59	Acceptable
40-49	Marginal
30-39	Unfavourable
20-29	Very unfavourable
10-19	Extremely unfavourable
< 10	Impossible

Source: Perch-Nielsen et al. 2010.

Mathematical adaptation

For the nine stations for which sunshine hour data are not available, the standard TCI equation cannot be used. The first iteration of the TCI equation developed by Mieczowski (1985) included 12 different climatic variables (Perch-Nielsen et al., 2010). Due to limitations in data availability for some of these variables, the model was adapted to include only seven variables (Perch-Nielsen et al., 2010). There is thus precedent for the mathematical adaptation of the equation to compensate for unavailable data, and for running the model on a smaller subset of climatic data.

The unavailability of sunshine hour data effectively removes the quantification of the aesthetic component of the TCI. We therefore proportionally distribute the weighting of the S-variable across the weightings for the remaining variables, which represent the thermal and physical aspects of climatic suitability for tourism. The resultant mathematically adapted equation is given by:

$$TCI=2(5(CD)+1.25(CA)+2.5(R)+1.25(W))$$

The maximum potential value of the final TCI that is calculated using the mathematically adapted formula remains 100 (Mieczkowski, 1985; Perch-Nielsen et al., 2010; Kovács & Unger, 2014). The rating scale can thus be used for values calculated under both equations.

Verification of adaptation

To determine whether the mathematically adapted model is sufficiently robust in quantifying the climatic suitability of a location for tourism, this adapted equation is applied to the nine locations for which sunshine hour data exists. The output values are then compared to those for each of the locations using the original model. As the datasets have a non-normal distribution, non-parametric methods of comparison are required (MacFarland & Yates, 2016). Comparison is undertaken first using the non-parametric Spearman correlation, with the strength of similarity determined using calculated p-values (Zar, 1972), calculated independently for each location using the annual TCI scores for the longest continuous data period. The second test explores the comparative means, standard deviations, and performs a pair-wise nonparametric comparison using the Wilcoxon matched-pairs signed-ranks test, under the null hypothesis of absolute relation between the two (MacFarland & Yates, 2016).

Results

The Spearman correlation coefficients comparing the results of the two models for each location reveal strong, statistically significant associations, indicating successful matching of the two datasets (Table 5). The strong, positive Spearman correlation coefficients indicate that the mean annual TCI scores calculated using each of the two methods behave in a consistent manner, ie. results from the two models are either identical, or vary in a consistent manner. The output of the Spearman correlation indicates that the mathematically adapted TCIs are an acceptable replacement for the standard TCI where sunshine hour data are not available.

Table 5
Spearman non-parametric correlation between the annual results of the traditional TCI and the annual results of the mathematically adapted TCI for the locations that had complete sets of data

Location (Time period)	Spearman correlation coefficient	p-value	Interpretation
Bethlehem (1981-2014)	0.99	<0.0001	Significantly associated
Bloemfontein (1992-2014)	0.95	0.0005	Significantly associated
Cape Town (1966-2014)	0.99	<0.0001	Significantly associated
East London (1959-2014)	0.94	<0.0005	Significantly associated
Johannesburg (1992-2014)	0.99	0.0005	Significantly associated
Kimberley (1959-2014)	0.96	<0.0005	Significantly associated
Polokwane (1993-2014)	0.96	0.0005	Significantly associated
Port Elizabeth (1959-2014)	0.98	<0.0001	Significantly associated
Port Nolloth (1999-2014)	1.00	0.0005	Significantly associated

In addition to exploring whether inter-annual changes in TCI scores for each of the locations behave similarly using the standard and mathematically adapted TCI, it is also of interest to test the variability in mean output scores using the two models. The Wilcoxon matched-pairs signed-ranks test explores the extent to which the median of the differences between the two models vary significantly from zero. Under perfect substitution within the mathematically adapted model, the variance of the median differences between the two would be non-significant. In this instance, the model would be deemed a highly accurate approximation of the standard TCI model. This is only the case for Kimberley and Bethlehem (Table 6). For the remaining stations, the variance in means is significantly large (Table 6). In all seven instances, this is the result of the mean TCI scores from the mathematically adapted index being significantly higher than those of the standard index (Table 6). As noted in the methods section, the omission of sunshine hour data effectively removes the aesthetic component of the index. These heightened scores obtained from the mathematically adapted model thus indicate that this prevents the negative compensation of less suitable sunshine hours for these stations. Interestingly, this is not concentrated only for stations for which cloud cover is notoriously unsuitable, such as Cape Town. Rather the omission of sunshine hour data inflates the TCI scores across all climatic regions of the country.

Table 6
Wilcoxon matched-pairs signed rank test output for the pairwise comparison of the standard and mathematically adapted TCIs

Location (Time period)	Mean standard	Mean adapted	σ standard	σ adapted	p-value	Interpretation
Bethlehem (1981-2014)	80.35	80.59	3.01	3.64	0.1099	Non-significant
Bloemfontein (1992-2014)	85.39	86.35	2.59	2.44	0.0002	Significant
Cape Town (1966-2014)	81.59	82.04	3.39	4.13	0.0024	Significant
East London (1959-2014)	77.50	80.27	3.88	4.36	<0.0001	Significant
Johannesburg (1992-2014)	84.48	86.35	4.06	4.30	<0.0001	Significant
Kimberley (1959-2014)	88.20	88.04	2.38	2.78	0.1600	Not significant
Polokwane (1993-2014)	86.64	88.55	2.56	2.48	<0.0001	Significant
Port Elizabeth (1959-2014)	80.05	82.55	3.28	4.24	<0.0001	Significant
Port Nolloth (1999-2014)	76.50	78.38	3.63	4.70	0.0001	Significant

Discussion

The results of this study indicate a statistically significant association between TCI scores calculated using the traditional equation, and those calculated using the mathematical adaptation proposed in this study to account for the absence of sunshine hour data. The veracity of these scores is explored in the forthcoming sections, with a focus on the limitations of the application of this mathematically adapted model, followed by a critical analysis of the appropriateness of the TCI in the African context.

Limitations in the adaptation of the model

The greatest limitation in the mathematically adapted TCI, both theoretically and practically, is the complete removal of the aesthetic component of climatic suitability for tourism. From a theoretical perspective, omitting sunshine hours means that the relative benefits and detriments of a long summer's day with clear skies compared to a short winter's day with full cloud cover are not accounted for. This aesthetic component is a critical factor in determining the seasonality of peak visitation, in making comparisons between locations for a given season, and in controlling the suitability of outdoor activities. Certain outdoor activities are particularly reliant on the aesthetic component, such as beach activities for which the potential for tanning is an important consideration. This is arguably particularly pertinent in the South African context, where not only is beach tourism a large sector, but where the identity of the tourism sector is closely linked to the clear skies as "sunny South Africa". With much of the African continent spanning the sub-tropics to tropics, and with many outdoor and nature-based attractions, the role of sunshine and the number of sunshine hours in attracting tourists is critical. Moreover, for desert regions, which span a considerable proportion of northern Africa, sunshine hours may compensate for the detrimental effects of very low humidity and high temperatures (Köberl, Prettenthaler & Bird, 2016).

From a practical stance, the limitation of the exclusion of the aesthetic component is highlighted in the results of the Wilcoxon matched-pairs signed rank test, with statistically significant variances in means for seven of the nine locations. Despite the predominance of statistically significant deviations between the two means, the consistency in the deviation means that the under-compensation of the detrimental effects of deleterious sunshine hours can be addressed through a correction factor. The mean variance in mean TCI scores for the two models for these nine stations is 1.38. It is thus recommended that when using the mathematically adapted TCI in the South African context, that an amount of, or close to, 1.38 be deducted from the final score. Where a station is very similar in climatic properties to one of those listed, the variance in means for the single listed station could effectively be used. Despite the similarities in variances between means for each of the nine stations, such a correction factor should not be used outside of South Africa, due to its relatively unique position in the mid-latitudes. Rather, for other countries on the African continent, the standard and mathematically adapted TCI should be used on a common dataset and the variance in means explored to obtain this correction factor.

To circumvent the limitations of the complete omission of the aesthetic component of the model, an alternative would be the use of a proxy for sunshine hours. The most obvious proxy would be measures of cloud cover. If these were available on an hourly basis, the reduction in sunshine hours on the basis of cloud cover could be reasonably accurately inferred. This reduction could then be applied to the daily sunlight hours for the location – the difference between sunrise and sunset time. Alternately, a separate ranking system could be developed for cloud cover as an aesthetic component itself, which could be substituted with sunshine hours with a compensatory adjustment to the weighting. However, this requires the availability of cloud cover data at a minimum of hourly temporal resolution. For the nine stations for which sunshine hour data were unavailable, no cloud cover data were available either. We suspect a similar case exists for much of the African continent due to difficulties in cloud cover measurement. Moreover, in subtropical regions, cloud cover is usually convective in nature, and thus the radius of the spatial scale of any cloud cover measurements is considerably smaller than for the measurements of other climatic variables. Working with climatic variables that are more commonly available, the potential for using rainfall as a proxy for cloud cover, and in turn sunshine hours, should be considered (Nicholson, 2000; Nicholson et al., 2012). If rainfall amounts and the rate of accumulation of rainfall water were able to be reliably associated with sunshine hours for a given location (once seasonal variations in length of day have been accounted for), this may provide a more easily accessible proxy. Finally, although omitting the effect of precipitation, the role of day length alone should be considered as a very simple inclusion of the aesthetic component, as it would account for relatively improved aesthetic conditions in mid-latitude and sub-tropical regions, relative to the poles.

The appropriateness of the TCI model in the African context

Despite the TCI being widely used, it has a number of fundamental limitations (Moreno and Amelung, 2009; Perch-Nielsen et al*.,* 2010; Rosselló-Nadal, 2014). One of the major limitations of the TCI lies within its subjective nature and due to its lack of verification (Perch-Nielsen et al*.,* 2010). The weightings of the five sub-indices are based on a combination of biometeorological literature and expert opinion (de Freitas et al., 2008; Rosselló-Nadal, 2014). Importantly, the weightings have been developed for the global North, much of which comprises significantly less suitable climatic conditions for tourism than the African continent, and which support tourism sectors that are consequently far less dependent on outdoor activities. Recent derivatives of the TCI attempt to eliminate the lack of verification against tourist perceptions with regards to ideal conditions for different tourist activities (Moreno & Amelung, 2009). Although Mieczkowski (1985) indicated that the TCI formula could be changed in terms of ratings and weightings for specific activities, this has only recently been explored (Moreno & Amelung, 2009; Rosselló-Nadal, 2014). For example, Morgan et al. (2010) altered the TCI by basing it on tourist preferences for climate conditions and swimming water temperature (which were obtained through questionnaires) and therefore altering the TCI to specific tourist market groups by using different weightings. Another area of criticism of the TCI is it cannot identify the potential overriding effects of certain climate variables during specific tourist activities (Moreno & Amelung, 2009). Furthermore, the TCI does not recognise the potential of geographical and intercultural preferences in climate (de Freitas et al., 2008). Again, efforts have been made to adjust the TCI to account for the potential of overriding effects and differences in climate preferences (Gomez-Martin, 2006; de Freitas et al., 2008). These factors are likely to be heightened for the African continent, with far greater heterogeneity in climatic conditions, tourist attractions, tourism accommodation establishment offerings, and cultural climatic preferences. In particular, the adaptation of the model presented here may be particularly weak in the African context due to the enhanced climatic suitability relative to much of Europe, resulting from a high mean annual sunshine hour value, an due to the predominance of outdoor attractions. However, the adaptation of a model necessarily required the initial implementation of the model in standard form to enable iterative development and comparative assessment. The index is thus probably not completely appropriate to the climatic context of the African context at present. However, adaptations to the model to compensate for difficulties in data acquisition enable more complex adaptations to be made to develop a regionally appropriate index.

It is important to note that the TCI cannot predict tourist arrivals (Amelung et al., 2007). The index merely serves to provide information on levels of comfort for tourism activity based on the climate. The TCI does not recognise the existence and quality of infrastructure that supports tourism, such as, accommodation and transport (Amelung & Nicholls, 2014). Therefore, a region may have a particularly high TCI score but can still experience low tourist arrivals as a result of a multitude of factors other than climate, including political instability, crime, and a lack of necessary infrastructure to support tourism (Amelung et al., 2007). Arguably, in the African context, these factors are heightened relative to the global North. Thus, the relative strength of influence of particularly suitable climatic conditions, relative to greater socio-political disincentives for tourists requires further exploration and quantification.

Conclusion

The TCI has been widely used in the global North to assess the climatic suitability of tourist destinations, and to facilitate the comparison of similar destinations on the basis of the relative climatic suitability. The uptake of this index as a methodological approach in Africa has not been forthcoming. This may in part be due to a relatively poor overall focus on themes of tourism and climate change across the country. However, the paucity of data is a significant detriment to the use and application of this index, and is likely to comprise a significant factor in the absence of literature applying this index for African locations, particularly due to the importance of climate in many African countries as a drawcard for tourism. This study presents a viable approach to the application of this index for locations for which no sunshine hour data are available, as confirmed by the statistical association of the two outputs. However, we caution that no more than one variable should be omitted, and that the implication of that variable in determining the multiple facets of climatic suitability for tourism must be considered. Moreover, we would argue that the possibility for running the model on a smaller dataset should not negate the importance of improving data networks to better quantify the role of climatic suitability in driving tourist flows, particularly under climate change.

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