

Review

GIS-Based Emotional Computing: A Review of Quantitative Approaches to Measure the Emotion Layer of Human–Environment Relationships

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Abstract: In recent years, with the growing accessibility of abundant contextual emotion information, which is benefited by the numerous georeferenced user-generated content and the maturity of artificial intelligence (AI)-based emotional computing technics, the emotion layer of human–environment relationship is proposed for enriching traditional methods of various related disciplines such as urban planning. This paper proposes the geographic information system (GIS)-based emotional computing concept, which is a novel framework for applying GIS methods to collective human emotion. The methodology presented in this paper consists of three key steps: (1) collecting georeferenced data containing emotion and environment information such as social media and official sites, (2) detecting emotions using AI-based emotional computing technics such as natural language processing (NLP) and computer vision (CV), and (3) visualizing and analyzing the spatiotemporal patterns with GIS tools. This methodology is a great synergy of multidisciplinary cutting-edge techniques, such as GIScience, sociology, and computer science. Moreover, it can effectively and deeply explore the connection between people and their surroundings with the help of GIS methods. Generally, the framework provides a standard workflow to calculate and analyze the new information layer for researchers, in which a measured human-centric perspective onto the environment is possible.

Keywords: human–environment relationship; collective emotion; GIS-based emotional computing

1. Introduction

The human–environment relationship has always been a key issue in geography in terms of the interaction between human society and its activities and geographical environment [1–3]. There is a significant body of literature that investigates such relationship from various aspects, including

evaluation [4], modeling [5], and application [6], and these studies provide a solid foundation for the burgeoning and interdisciplinary fields, such as quality of life (QOL) [7].

Presently, there are two main forms to measure the interaction between human and environment: the objective indices of environment attributes, such as evaluation index systems, and the subjective indices from human perceptions, such as sense of place. As for the former, the evaluation index systems usually are composed of indices that cover aspects such as accessibility, density, land use, and land cover changes, and economics [8,9]. Nevertheless, the selection of such indices is limited to current understanding of the interaction between humans and environment. In other words, human–environment relationship may be underrepresented with such methodology. As for the latter, the literature delivered various questionnaires to obtain indigenous people’s sense of place in three place constructs: place identity, place dependence, and place attachment [10]. Although subjective indices like sense of place seem to draw a synthetical picture of human–environment relationship from the humanistic perspective, they emphasize portraying people’s abstract emotional connection with their inhabited locality. Similarly, the items of questionnaires are still constrained by the state of knowledge.

On the one hand, the concept of “place” is more than a location or a restricted space but a reality to be understood from the perspectives of people. “Place” reflects the way people perceive and experience the surrounding environment [11]. On the other hand, emotion, which dramatically influences human consciousness [12], serves as a bridge between the environment (both physical and social environment) and the final experience that a person obtained from the environment [13–17]. Therefore, exploring collective emotion of places plays a conspicuous role in human–environment relationship research. With the advent of big data era and the maturity of artificial intelligence (AI)-based emotional computing techniques, massive individual-level emotional information is available to scientists. Over the last decade, emotional computing has gained momentum, and it provides possibilities for developing a new layer of emotion information for human–environment relationship research.

In this paper, we present a novel research framework, which equips collective emotion with geographic information system (GIS) methods to quantitatively measure the emotion layer of human–environment relationship, namely GIS-based emotional computing. This framework aims to provide a standard workflow for calculating and analyzing the new information layer in different geographical granularities. These results allow further study about understanding human behavior in a certain environment and planning from a human-centric perspective. Crucially, we expect that this framework provides complementary information to existing methodologies, rather than supplant them (see Figure 1). We define the term GIS-based emotional computing as a data-driven methodology that extracts emotional characteristics in places and analyzes it with GIS methods. Compared to affective computing proposed by Picard [18], GIS-based emotional computing focuses on collective emotion in places rather than individual emotional states. We advocate that the GIS-based emotional computing can be a prominent research framework, and a useful tool, for dynamic diagnosis of the human–environment relationship in different geographical and temporal granularities, with collective emotions obtained from on-the-fly user-generated contents (UGCs).

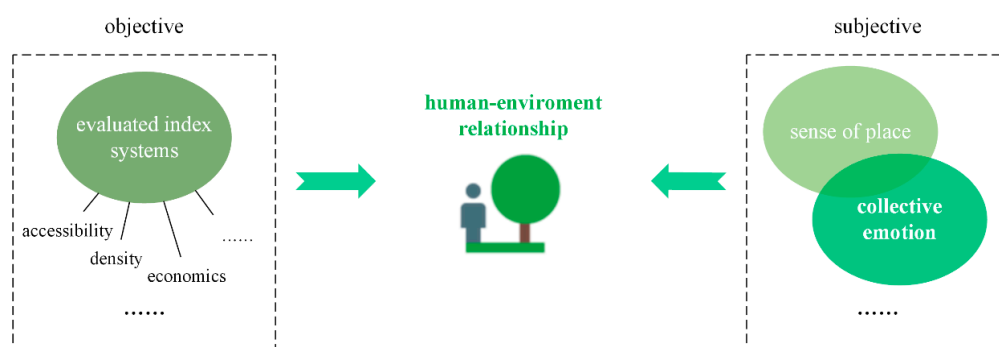


Figure 1. The methodologies of quantitatively and qualitatively describing human–environment relationship.

As illustrated in Figure 2, the framework comprises three key steps: first, collecting environment and emotion related data in various context from data sources such as social network sites and official sites; second, exploring and cleaning data and extracting emotional information from georeferenced emotion related data based on its data structure; and third, conducting spatiotemporal analysis using GIS methods such as spatial interpolation and kernel density analysis in order to provide researchers with additional insights into the complex human–environment relationship. To elaborate the contents of each step, the rest of this paper is structured as follows. In Section 2, step 1 and step 2 of GIS-based emotional computing will be stated. Specifically, we classify three types of data sources of human emotions in the existing literature and elaborate their current advantages and weakness. On the basis of data sources and data structure, we introduce several popular methods of emotion recognition. Additionally, Section 3 presents the step 3 of GIS-based emotional computing, and three analysis directions show the potential of GIS methods in emotion analysis. Section 4 summarizes the current challenges and opportunities on GIS-based emotional computing. Finally, in Section 5, we end the paper with a number of key conclusions.

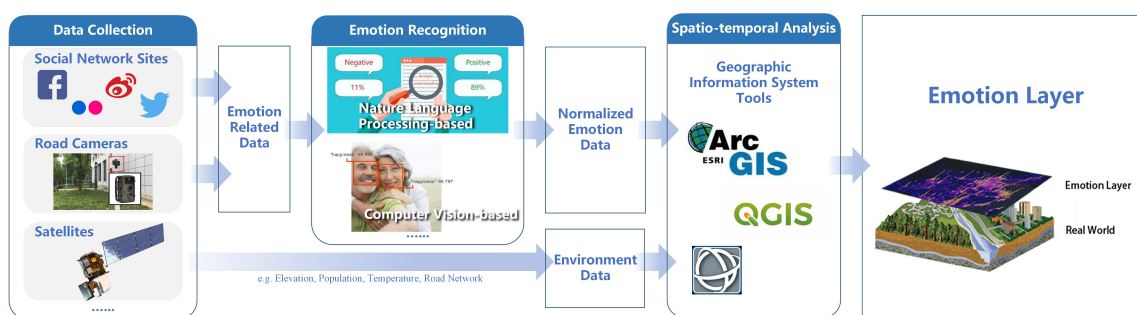


Figure 2. The conceptual framework of geographic information system (GIS)-based emotional computing.

2. Emotion Recognition

Emotion organizes our cognitive processes and action tendencies [19] and influences individuals' social interactions in systematic ways [20–23]. Furthermore, studies suggest that emotional expressions have a potential impact on personality, even can predict life outcomes (e.g., marriage and personal well-being) of decades later [24,25]. Since measuring a person's emotional state is one of the most vexing problems in emotional studies, emotion recognition plays a dominant role in GIS-based emotional computing. Generally, the data sources of human emotions include the following three types: self-report, body sensor, and UGC. According to data structure, the methods of emotion recognition can be classified into four types: self-reported, body sensor-based, UGC text-based, and UGC image-based. As such methods continue to be improved, we will introduce several popular methods of each type in this section.

2.1. Self-Reported

Self-report usually collects emotional information by online or offline questionnaires and interviews. It is a traditional and classic data source. Although alternative data sources of human emotions emerged one after another, self-report remains a popular choice.

A substantial body of research on self-reported emotional information proves its easy interpretability, the richness of information, and sheer practicality [26–28]. For example, a recent study obtained the daily time, location, activity, mode of transportation, and emotions of female sex workers in their diaries [29]. However, the response rate of questionnaires, in most studies, remains relatively low [10,30], and these studies rest upon the assumption that respondents can represent those who refused to respond. Moreover, prior literature has also shown that people have blind spots in their self-knowledge, and they may not always understand their emotional states very accurately [31,32].

There are two mainstream self-reported scales widely utilized in emotional research. One common test called Satisfaction With Life (SWL) was put forward by Diener, Larsen [33]: its score reflects the

extent to which a person feels that his/her life is worthwhile [34,35]. Continued efforts have been made by scholars and policymakers to measure and promote subjective well-being for individuals and groups at the community level with the help of SWL [36,37]. Applications of SWL have been implemented at regional, national [38], and global levels [39–41].

However, the SWL test is restricted to only rate people's happiness. A two-factor model of Positive and Negative Affect Schedule (PANAS), developed by Watson et al. [42], has been used more extensively according to the self-report emotion literature. This model is comprised of two 10-item emotion scales. These items are words that describe different feelings and emotions in Positive Affect (PA) and Negative Affect (NA), such as interested and irritable to describe a person's emotional state. Updated versions of the PANAS were developed. For instance, to assess specific emotional states, Watson et al. [42] created a 60-item extended version of the PANAS (the PANAS-X) that can measure 11 specific emotions including fear, sadness, guilt, hostility, shyness, fatigue, surprise, joviality, self-assurance, attentiveness, and serenity. Meanwhile, a 30-item, modified version of the PANAS designed for children (PANAS-C) was proposed by Laurent et al. [43], and provides a brief, useful way to differentiate anxiety from depression in children.

2.2. Body Sensor

In recent decades, with the motivation of making computers that can assess and even understand users' emotional states, existing literature of human-computer interaction (HCI) has applied sensing technology to collect users' physiological signals in different emotional states [44–46]. Stationary and wearable sensors are both commonly utilized to collect the changes in the physiological signals of users [47]. As an example, a wearable sensor platform was developed by Choi et al. [48], which monitored mental stress.

Even if people do not explicitly express their emotions through facial expressions, changes in their physiological patterns are inevitable and collectible [49]. However, the inherent noise in physiological signals and their non-standard data structures has hampered the wide utilization of such data [49]. Even more, they can only provide datasets with limited sample sizes and short time durations [50–52].

There is a popular workflow of body sensor-based methods. Once the physiological signals were collected from multi-sensory devices, signal processing methods were used to extract applicable features from the physiological signals. Then, machine learning algorithms utilize, such features as model inputs to predict emotional state. Generally, five types of physiological signals are widely captured because they are show the correlation of underlying emotional fluctuations [53], including: (1) cardiovascular activities, (2) electrodermal activities, (3) the respiratory system, (4) the electromyogram activities, and (5) brain activities. Likewise, there are numerous options of signal processing methods (e.g., Fourier transform, wavelet transform, thresholding, and peak detection) and machine learning algorithms (e.g., k-nearest neighbor, regression trees, Bayesian network, and support vector machine) in the workflow [49]. For instance, Choi et al. [48] used the k-nearest-neighbor algorithm and the discriminant function analysis to analyze the physiological signals such as galvanic skin response and heat flow, when classifying the emotions.

2.3. UGC Text-Based

When entering the 21st century, the increasing development of social networking sites (SNS) provides unprecedented opportunities to collect massive individual emotional information. Geo-tagged UGC (e.g., microblogs, blogs, and reviews) usually collect from various SNS such as Twitter, Amazon, Weibo, and Flickr.

These UGC offer rich information about users' emotions in different settings such as family, work, and travel. Moreover, those petabytes of data have high spatiotemporal resolution, and their collection is convenient and timesaving. Nevertheless, abundant evidence shows that the bias (including emotional bias) exists in big data, and its spatial sparsity still needs to be addressed [54]. Furthermore, although geo- information shows that UGC can be related to places, emotions may not

be directly affected by the surrounding environments since they may be influenced by the activities at specific places. As for UGC text, it is difficult to extract emotional information within complex sentences (e.g., multiple negations and metaphors). There is no common model or algorithm to detect emotions in different languages. Besides, the same sentence may have different meanings in diverse contexts and cultures.

Early research in this area focused on identifying and quantifying the polarity (i.e., positive or negative) of natural language text. For example, Pang, Lee [55], and Read [56] utilized support vector machine and Naïve Bayes (NB) classifier to extract emotional polarity from large volumes of movie reviews and emoticons. Since human emotions are very subjective and complex, setting just positive, negative, and neutral categories is too coarse to capture the full details of human emotions [57]. Recently, there has been an increased emphasis on extracting multi-dimensional human emotions from text by developing emotion lexicons such as WordNet-Affect (WNA) [58], EmoSentNet (ESN) [59], and word-emotion lexicon [60].

Moreover, there is research that aims to improve the existing emotion lexicons to make it suitable for different settings. For example, a novel emotion lexicon was developed by Chakraverty et al. [61], which was compiled by integrating information from three aspects: the domain of psychology, the lexical ontology WordNet, and the set of emoticons and slangs commonly used in web jargon.

2.4. UGC Image-Based

UGC images contain the advantages and disadvantages of UGC we discussed above. With regard to images, their quantity is less than UGC text. Although images are informative, they resist interpretation. With the development of technology in computer vision, image-based emotion extraction methods are becoming more and more mature. Detecting facial expressions is a fashionable image-based extraction method. Human faces provide one of the most powerful, versatile, and natural means of communicating a wide array of mental states [62], and the relationship between facial muscles and discrete emotion in various cultures is consistent [63]. Most of the techniques on facial expression-based emotion extraction methods are inspired by the work of Ekman et al. [64], who produced the facial action coding system (FACS). Still, many early facial-expression datasets [65,66] were collected under “lab-controlled” settings where participants were asked to artificially generate some specific expressions, which do not provide a good representation of natural facial expressions [67]. In recent years, several studies have utilized robust computational algorithms to automatically capture human emotions from individuals’ facial expressions in photos. Recent efforts like that of Yu [68] have proposed a method that contains a face detection module based on the ensemble of three face detectors, followed by a classification module with the ensemble of multiple deep convolutional neural networks (CNN). What’s more, several commercial application programming interfaces (APIs), such as Face++ Detect API [14] and Microsoft Azure Emotion API [69], are available for scientific research.

3. Analyzing Collective Emotion with GIS

Generally, there are following three analysis directions in the current emotion studies of human–environment relationship: (1) the temporal and spatial distribution of human emotions, (2) the impact of environment on collective emotion, and (3) collective emotion as indicator. In this section, we will illustrate how to apply GIS methods to these studies.

3.1. The Temporal and Spatial Distribution of Human Emotions

Due to the changes of the environment, people may have different emotional experiences at different times and places. Understanding the distribution of human emotions is a basic topic in GIS-based emotional computing, and it is broadly observed at different granularities in the existing literature [70–73]. For example, the diurnal and seasonal rhythms of the changes in individual-level emotions can be identified by natural language processing from Twitter text [74]. Additionally, Flickr photos with geotags are traced and analyzed to extract the trend in the changes of human

emotions between 2004 and 2014 [75] at the international level. Moreover, the World Happiness Report [40] surveys the state of global happiness. Visualization of the spatiotemporal distribution of human emotions at the national scale is widely carried out in different countries [38,76,77]. Moreover, researchers have begun to study the distribution of human emotions at fine granularities including communities and parks [78,79]. However, the previous emotion maps either displayed the discontinuous sample points or a simple regionalization of emotions averages to various areal units at a certain scale because of spatial sparsity of the sampling data. In the GIS-based emotional computing framework, evenly distributed sampling points and GIS methods, such as spatial sparsity would be used to improve the accuracy. Further improvements will be discussed in Section 4.

3.2. The Impact of Environment on Collective Emotion

Scholars have shown that the surrounding environment has impacts on collective emotion [10–12]. It appears that both physical and social environmental factors are related to collective emotion [80–82]. On the one hand, literature from environmental psychology has explored the interactions between collective emotion and physical environmental factors such as naturalness [83], density, accessibility, and so forth. Most of these studies suggested that happiness is lower in less natural landscapes, denser populations, and in areas with more traffic inconveniences. On the other hand, the relationships between collective emotion and socio-economic attributes have been reported widely in social science. For instance, Easterlin [13] found that there is a significant positive association between income and happiness within countries. Table 1 shows what kinds of environmental factors and at what scales have related works examined the impact of environment on human emotions.

Table 1. Previous works on the impact of environment on human emotions.

Data Source	Sample Size	Study Area	Results	Citation
Flickr photos	2,416,191 faces	Global	Environmental factors such as natural landscape and water body have significant impact on tourists' happiness.	Kang et al. [84]
Flickr photos	60,013 images	Greater Boston Area, the United States	Components of exposure to nature including green vegetation, proximity to water bodies, and undeveloped areas have a robust, positive effect on happiness.	Svoray et al. [82]
self-report app records	1,138,481 responses from 21,947 users	The United Kingdom	The relationships between environmental factors (land cover type and weather) and happiness are highly statistically significant.	MacKerron, Mourato [85]
self-reports	25 participants	Dundee, the United Kingdom	More green space in the surrounding environment can help people to adapt to stress.	Ward Thompson et al. [86]
self-reports	158 participants	NA	There is a positive, linear association between the density of urban street trees and self-reported stress recovery.	Jiang et al. [87]
tweet text of Sina Weibo	210 million microblog tweets	China	Air quality is associated with happiness.	Zheng et al. [80]
self-reports	NA	Multiple countries	Air pollution plays a statistically significant role as a predictor in subjective well-being.	Welsch [88]
self-reports	564 households	Communities in Ann Arbor, Michigan, the United States	Having natural elements in the view from the window contributes to residents' sense of well-being.	Kaplan [89]
self-reports	953 participants	Nine Swedish cities	Statistically significant relationships were found between the use of urban open green spaces and self-reported experiences of stress.	Grahn, Stigsdotter [90]

Table 1. Cont.

Data Source	Sample Size	Study Area	Results	Citation
self-reports	over 10,000 individual adults	The United Kingdom	The individuals are happier when living with greater amounts of urban green space.	White et al. [36]
self-reports	17,000 individuals	The Netherlands	Self-reported distress is greater in areas with lower levels of green space.	de Vries et al. [91]
tweet text of Twitter	34 metropolitan statistical areas	The United States	Climate factors like relative humidity and temperature contribute to local depression rates.	Yang et al. [92]
self-reports	NA	The United States	There is a significant positive association between income and happiness within countries	Easterlin [13]

NA—not available.

Nevertheless, such studies are usually limited to a fixed granularity, and it is difficult to tell whether scale affects the interactions between collective emotion and environmental factors. Furthermore, the interactions are mostly qualitative rather than quantitative. With integrating GIS methods to emotion analysis, solving these problems can be possible. For example, as for the interaction between collective emotion and the accessibility of an environmental feature such as a water body or green vegetation, separately establishing several buffers will help us to explore how distance from an environmental feature has an impact on collective emotion.

3.3. Collective Emotion as Indicators

Since Goodchild [93] proposed the concept of volunteered geographic information (VGI), which suggests that general individuals can be compared to environmental sensors, a variety of studies have tried to explore urban development patterns using individual-level big geospatial data, called “social sensing” [94]. In the context of human–environment relationship, collective emotion has been served as a system of indicators describing the interaction of human and environment and supporting policymakers to make decisions [95].

Collective emotion provides a new insight to understand crisis events that range from natural disasters to man-made conflicts and how people respond to such rapid environment changes [96,97]. For example, Chien et al. [98] evaluated sentiment analysis of Flickr text in disaster management at the time of the strike of a typhoon in Taiwan, China in 2009. Likewise, Dewan et al. [99] analyzed the emotion of textual and visual content obtained from Facebook during the terror attacks in Paris, France, 2015.

In recent years, collective emotion in places is gradually applied to guide urban planning [100,101]. A recent work analyzed the spatial characteristics of residents’ emotions in the city and at different types of places in the city of Nanjing, China, to provide evidence that could help optimize urban space development [102]. Likewise, another research measured pedestrians’ emotions, and results offered initial evidence that certain spaces or spatial sequences do cause emotional arousal [103]. A semantic and sentiment analysis was conducted to understand the perceptions of people towards their living environments by examining online neighborhood textual reviews [79] and nearby neighborhood street view images [104].

Although discovering valuable insights, these studies have great possibilities to obtain more accurate results by GIS-based emotional computing. Firstly, the framework focuses on the multisource data collection methods, which improve the volume and tolerance to the noise of emotion data. Moreover, the integration of multiple disciplines, such as GIScience, computer science, and social science, brings excellent calculation and analysis abilities that enable researches to perceive dynamic and complex responses to places in near real-time. For instance, poorly timed traffic lights at crossroads and a situation of severe earthquake both became detectable for immediately deciding the assistance policies.

4. Challenges and Opportunities

While GIS-based emotional computing offers rich insights into a better understanding of human–environment relationship, it poses a number of challenges, highlighted below: firstly, different emotional baselines may exist in different regions and even between individuals. In other words, emotional experiences may be influenced by many factors such as individuals’ memory, life history, culture, age, and gender. Diener, Diener [105] found that self-esteem is strongly related to subjective well-being (analogous to general positive emotions such as happiness) in individualist cultures (such as the United States), but only has limited effects in collectivist cultures (such as China). In fact, prior literature has shown that how and when emotions are experienced may differ from one culture to another [106–109]. This difference is also affected by population’s age and gender characteristics [110,111]. Therefore, researchers should take the demographic composition and culture of different places into account when conducting research with GIS-based emotional computing.

Spatial sparsity of data on human emotions is an important issue to be solved. Although emotion maps have been created by studies at different spatial scales [84,112], the sampling data is an occurrence collection. In other words, these are presence-only data without absence data. Therefore, the previous emotional studies were either the interpolations of sampling points, which inevitably involved overfitting, the discontinuous display of sample points [112], or simply the regionalization of emotions averages to various areal units at a certain scale [113]. However, for emotional expressions that cannot be observed, it is hard to determine the emotions that are associated with places. In a recent work, Li et al. [114] utilized MaxEnt [115], a species distribution model, which is intensively applied in ecology, to map the geographic distribution of human emotions at a global scale but fell short of applying to other granularity such as city and community. Yet, there is still no model available that all scholars have agreed upon through a consensus to describe and predict the continuous distribution of human emotions based on presence-only data.

Another challenge is that spaces with various land use mix (LUM) [116] may trigger different emotions. People usually express emotional responses to “place” rather than “space” [8], but multiple places may overlap in the same space at different times. For a specific street, people may stay on the street for work during the daytime while visiting bars at night. The locale and its spatiotemporal dynamics may influence human emotions and are supposed to be taken into consideration for GIS-based emotional computing.

It is important to note that SNS emotional information may bring systematic bias for GIS-based emotional computing. SNS users as a sample may not be representative of the total population [117,118]. Besides, due to the potential social pressures imposed by SNS [119,120], users may suppress or exaggerate their emotions. For instance, Huang et al. [121] suggest that the majority of Weibo users tend to post more photos with positive emotions instead of negative emotions, and there are significant differences in place emotion extracted from Weibo and in-situ. Since there is no model that is suitable for all places to rectify the emotions extracted from SNS yet, it is wise to pay attention to the bias of big data when conducting emotion research.

The impact of GIS-based emotional computing is multi-fold. With the help of the framework, the informative emotion layer of human–environment relationship can potentially enrich a variety of fields such as traffic planning, urban safety, human-centric tourism, and evaluating current planning projects. On the one hand, GIS-based emotional computing aims to collect massive multisource georeferenced data and provide state-of-the-art, multidisciplinary techniques for effectively and accurately detecting normalized emotion information from such data. On the other hand, the map from individual emotion to place emotion is promised by using GIS-based spatial analysis. Furthermore, geostatistics is a useful tool for deducing the causality between collective emotion and environmental factors.

There are several opportunities in the current development of GIS-based emotional computing. There has also been research into the connection between human perception and urban space through urban street view imagery, which is another promising dataset that can be employed in GIS based

emotion computing [104,122]. Building a multi-source emotional data fusion model can greatly advance the development of GIS-based emotional computing. A good way to obtain a wide range of human emotions in real-world settings is by combining big data (human emotions extracted from UGC) with small data [123] (human emotions captured in reality) based on different cultures and demographic characteristics to calibrate online emotion. Moreover, why people are satisfied with some places instead of others has not yet been extensively investigated. It remains unclear which environmental factors will influence people's emotions at all scales and how to properly quantify the extent of their influence.

5. Example of Implementing GIS-Based Emotional Computing

The emotion information analyzed by GIS-based emotional computing plays an increasingly vital role in human–environment relationship research, and it serves as a critical component of various applications including resource management, conservation, human geography, crime analysis, real estate, psychology, environmental justice, etc. Hereby we give an example that exhibits the potential to quantify human emotion and serves as a layer in GIS for human–environment relationships study.

The recommendation of tourist sites is a key topic in tourism studies. With GIS-based emotional computing techniques, georeferenced contents uploaded by tourists to photo services in the public domain enrich traditional recommendation systems with an emotion layer. One of our previous studies collected Flickr photos of 80 tourist sites all over the world, and applied spatial clustering to emotion information extracted from photos, for constructing an emotion layer for these tourist sites. Afterward, a map of tourist sites with emotion tendency and a ranking list of global tourist sites based on emotion were drawn, which serve as references for potential tourists. By calculating and analyzing the emotion layer and other layers in GIS, we have also attempted to identify, which natural and non-natural environmental factors may have an impact on visitor's emotions [84]. The workflow of the example can be seen in Figure 3. This example illustrated that, with GIS-based emotional computing, it is possible to cater to tourist preferences for accurate advertising and management of the tourist industry.

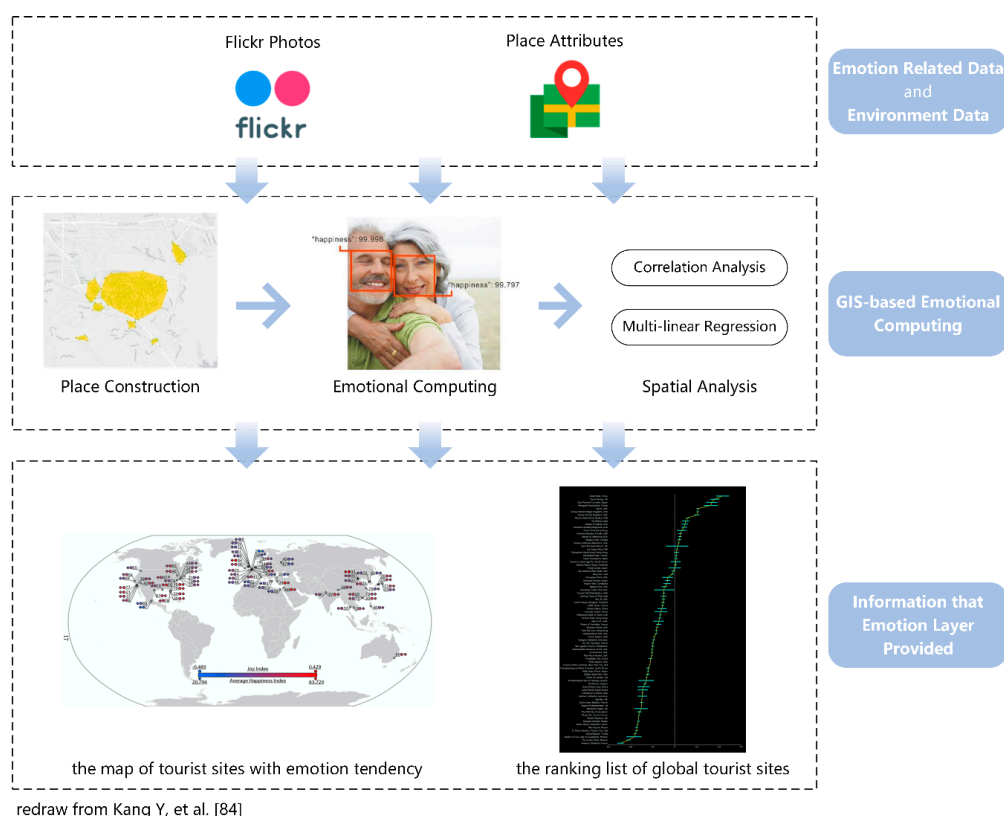


Figure 3. The workflow of an example implementing GIS-based emotional computing.

6. Conclusions

In this paper, we propose a new conceptual framework: GIS-based emotional computing, for providing a new approach to measure the emotion layer of human–environment relationship. The methodology comprises three steps: (1) collecting environment and emotion related data from different data sources, (2) detecting emotional information from georeferenced emotion related data by AI-based emotional computing techniques, and (3) conducting spatiotemporal analysis using GIS. The current literature related to each step was reviewed, and the improvements of GIS-based emotional computing can be done were discussed. The emotion layer reveals deep interactions between human and their surrounding environment, and it reveals “what people real feel” instead of “what people would feel”. GIS-based emotional computing consolidates the cutting-edge technologies of multidisciplinary, such as GIScience, sociology, and computer science, for providing a more effective and accurate avenue to calculate and analyze the emotion layer. It is important to note that GIS-based emotional computing of this scope has only been possible recently, due to the increasing capability of both massive UGC with emotional information and the technologies that take advantage of these resources. This implied that GIS-based emotional computing may have unlimited potential because of developing and advancing technologies. However, while the promise of collective emotion in describing the human–environment relationship is alluring, the challenges above have to be addressed for increased uptake of GIS-based emotional computing.

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