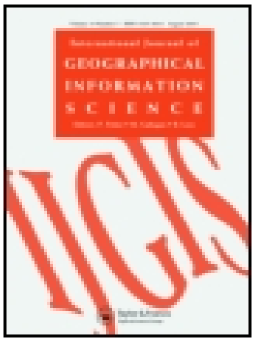

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RESEARCH ARTICLE

Emotional habitat: mapping the global geographic distribution of human emotion with physical environmental factors using a species distribution model

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ABSTRACT

Human emotion is an intrinsic psychological state that is influenced by human thoughts and behaviours. Human emotion distribution has been regarded as an important part of emotional geography research. However, it is difficult to form a global scaled map reflecting human emotions at the same sampling density because various emotional sampling data are usually positive occurrences without absence data. In this study, a methodological framework for mapping the global geographic distribution of human emotion is proposed and applied, combining a species distribution model with physical environment factors. State-of-the-art affective computing technology is used to extract human emotions from facial expressions in Flickr photos. Various human emotions are considered as different species to form their 'habitats' and predict the suitability, termed as 'Emotional Habitat'. To our knowledge, this framework is the first method to predict emotional distribution from an ecological perspective. Different geographic distributions of seven dimensional emotions are explored and depicted, and emotional diversity and abnormality are detected at the global scale. These results confirm the effectiveness of our framework and offer new insights to understand the relationship between human emotions and the physical environment. Moreover, our method facilitates further rigorous exploration in emotional geography and enriches its content.

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Affective computing; emotional distribution; species distribution model; geosocial data; maximum entropy modelling

1. Introduction

Human emotion constitutes a kind of comprehensive psychological and physiological state from neural systems that is triggered by human thoughts and behaviours (Izard 2013). Developing an understanding of human emotions has long represented a major focus of psychological research, being deemed helpful in organising and guiding individual's behaviour, communication and cognition (Arnold 1960). Among the numerous

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areas of study about the causes of emotions, emotional geography has sought to associate emotions with the specific environments that influence them (Milton 2005, Conradson 2016). Indeed, in emotional geography, human emotion is regarded as a bridge to link places to human perceptions (Davidson *et al*. 2012, Löw 2016, Svoray *et al*. 2018, Zhang *et al*. 2018). It also provides a new tool to analyse human psychology from a unique perspective, for many related disciplines, including research on public health (Carrus *et al*. 2015), human behaviour (Grossman 1977), social sensing (Liu *et al*. 2015), urban planning (White *et al*. 2013), transportation (Greg et al. 2018), the stock market (Bollen *et al*. 2011) and marketing (Banerjee *et al*. 2015).

Assessing and detecting human emotions can prove particularly challenging due to their intangible nature. Traditional research usually relies on self-reports, questionnaires or the measurement of physiological indices to obtain human emotion quantitatively (Lazarus 1982, Watson *et al*. 1988, Feldman 1995, Niedenthal *et al*. 2018), such as by offering an emotional mouse to computer users (Mizna *et al*. 2014), monitoring blood flow or pupil diameter (Bunney *et al*. 1967), or observing cerebral activity (Lee *et al*. 2006). However, these methods require considerable time and effort, and may be very sensitive to experimental settings (Nummenmaa *et al*. 2014). In the last decade, huge amounts of texts and photos have been published online and can be collected from social media networks such as Facebook, Twitter and Flickr. Such geo-tagged user generated content (UGC) certainly contains considerable detailed information about human subjective feelings and emotions, and hence may be used as raw material for emotional analysis (Goodchild 2010, Liu *et al*. 2015). Along with the advancement of machine learning and affective computing technology, it is now feasible to mine and quantify human emotions from these UGC data (Picard 2000, Li *et al*. 2013). On the one hand, some natural language processing (NLP) tools have been developed to measure emotions from online comments (Serrano-Guerrero *et al*. 2015) or published tweets (Doytsher *et al*. 2017). On the other hand, human emotions can be measured directly from human faces in photos using facial recognition technology (Kang *et al*. 2017, Singh *et al*. 2017). Studies have demonstrated that facial expression is a more accurate and effective way to extract human emotions (Izard 1990, Goeleven *et al*. 2008). Compared with textual data analysis, measuring emotions from photos presents the advantages of global universality and consistency across cultures (Elfenbein and Ambady 2002). Strong evidence has shown that there is a pan-cultural element in emotional expressions in photos all over the world (Ekman and Keltner 1997) and people have hold similar basic facial expressions through the ages (Preuschoft 2000). Thus, photos are more convenient for emotional geography research at a global scale.

Cognitive mapping can be dated back to Lynch (1960), who introduced 'image mapping' to capture the environmental perceptions of residents on the street scale. Since then, researchers have discovered that all cognitions in the environment are evaluative. Recently, emotion maps from UGC data have been created (Doytsher *et al*. 2017, Kang *et al*. 2019). Environmental factors that affect human emotions at different scales have been identified, including natural conditions (Svoray *et al*. 2018), socio-economic factors (Mitchell *et al*. 2013), cultural background and interpersonal environment (Singh *et al*. 2017). However, given that data regarding human emotions do not distribute at the same sampling rate/density in all regions around the world, current emotional maps either represent the geo-visualisation of existing data, the discontinuous display of sample points after extracting and filtering (Doytsher *et al*. 2017), the interpolations of sampling data (which inevitably leads to overfitting), or simply the regionalization of average emotion values to various areal units (Mitchell *et al*. 2013). A global-scale, continuous and balanced map that reflects the role of space and place for human emotion does not exist at present. Therefore, it is necessary to propose a methodological framework to explore the geographic distributions of various human emotions, considering the environmental factors in the same granularity at the global scale. Through such a framework, emotion distribution, especially in areas that lack emotion sampling data, can be mapped. Furthermore, questions like 'What is the distribution pattern of a kind of human emotion across an entire geographic space?' can be answered.

Although species distribution modelling (SDM) methods have been widely proposed and applied in studies of ecology, SDMs and cognitive mapping have only been developed in parallel. SDMs essentially use species presence-only sample data and environmental features to estimate species' niches and reflect the suitability of their potential habitats according to specific algorithms (Elith and Franklin 2013). Clearly, human emotions and species are not the same research targets, although several important research similarities between them do exist:

- Complexity: they are both affected by multi-dimensional environment factors (Hirzel and Le Lay 2008);
- Fuzziness: the distributions do not have hard boundaries, but merely probability representations in the corresponding environment (Elith and Franklin 2013);
- Dynamics: their distributions will change along with environmental changes (Hirzel and Le Lay 2008);
- Occurrence-only samples: their sampling data are often occurrence collections, namely, presence-only data without absence data, especially in poorly sampled regions. Moreover, these data cannot be directly applied and transformed into previous fitting models (Li *et al*. 2011);
- Space coexistence: multiple species can share the same habitat but occupy different ecological niches; likewise, various human emotions can co-exist and be co-expressed in the same space (Fithian *et al*. 2015).

Therefore, we believe that SDMs can bring new directions for mapping the distributions of human emotions. If different emotions are regarded as different 'species', one can model the 'habitat' of each emotion in the geographic space, termed as the *Emotional Habitat*, as well as its suitability.

The objective of this research is to depict the global geographic distributions of various human emotions quantitatively and accurately, using human facial expressions extracted from Flickr photos as raw material and applying the ecological modelling technique as a methodology. More specifically, a general framework, mapping the relationship between human emotions in places based on facial expression computing technology and specific physical environment factors with spatial modelling, is proposed and applied. The contributions of our study are three-fold. First, we propose a novel framework for mapping the distributions of emotions, leveraging SDM methods from the field of ecology. This will offer new directions and thoughts to emotional geographies. Second, we depict the global distributions of various emotions, including happiness and sadness, alongside physical environmental factors that can effectively reflect the human-land relationship. Third, the distributions of emotional diversity and abnormality are detected and analysed.

2. Related work

2.1 Human emotion research

Emotion is a kind of psychological state of human being, and is regarded as the responses and attitudes towards objective events and environments. Human emotion distribution is an important part of human psychological research, playing an important role in guiding people's behaviour and cognition (Ekman and Davidson 1994) and understanding residents' environments (Zeng *et al*. 2008), which has often been studied at different scales, such as the body (Nummenmaa *et al*. 2014), an area (Doytsher *et al*. 2017) or even at a global scale (Kang *et al*. 2018). Traditionally, numerous surveys on the distributions of emotions are published based on questionnaires and self-reports. For example, the World Happiness Report published by the United Nations (UN) ranks the happiness of every country with gross national happiness indices (Helliwell *et al*. 2012), while Gallup and Healthways attempt to quantify the well-being of different areas in the United States using polling data (Mitchell *et al*. 2013). However, these methods are costly in terms of resources and time, and may be implemented based on self-knowledge (Robinson and Clore 2002, Baumeister *et al*. 2007) and collected from limited samples in every administered district.

The development of artificial intelligence and machine learning technology provides a new perspective regarding emotion recognition and computing. There are now various computational tools available to detect human emotions and quantify their intensity automatically, which can be roughly divided into two categories according to the data type. One is the use of NLP methods to assess human emotions, such as well-being and depression, from texts via emotional dictionaries (Allisio *et al*. 2013, Mitchell *et al*. 2013, Cambria *et al*. 2014) or keyword extraction (Yang and Mu 2015, Doytsher *et al*. 2017). For example, the World Well-Being Project (http://wwbp.org/) has measured psychological well-being and physical health based on the analysis of languages in social media like Twitter and Facebook. Another is applying image-based approaches for facial expression recognition, including facial smile detection (Eckhardt *et al*. 2009, Abdullah *et al*. 2015) and emotion dimensional computing (Singh *et al*. 2017). Several facial image datasets have been collected and formed with their geographical locations like GeoFaces (http://geofaces.csr.uky.edu/). Compared with text analysis that may be edited and produced by lag, the facial expressions can be recorded in real-time when emotions are elicited (Berenbaum and Rotter 1992). These facial images can be tracked down and applied to map human emotions into geographic space and measure their spatiotemporal characteristics. For example, Svoray *et al*. (2018) have analysed the relationship between facial emotion from photos uploaded on Flickr and three environmental factors: greenness, distance from water and urban development. Furthermore, Kang *et al*. (2019) have ranked the happiness of 80 tourist attractions around the world based on 6 million social media photos. Also, facial expression in photographs can be regarded as an effective index to measure genuine human emotions, which are universal and spontaneous compared to text-based methods. Thus, by leveraging high-volume image data from social media platforms and using affective computing tools, human emotions can be detected and represented fully at a global scale.

2.2 Species distribution model

In the field of ecology, habitat modelling is a core scientific issue for studying the relationship between biological preferences and habitat environmental features (Hirzel and Le Lay 2008). There are three main research directions in habitat modelling: first, predicting the occurrence probability of species based on biological and environmental variables (Young and Carr 2015); second, depicting and understanding the relationship between species and habitats (Duffy and Chown 2017); third, quantitatively representing the species' habitat requirements (Liu *et al*. 2011). These SDMs predict environmental suitability for the species from the given physical variables based on different algorithms, including BIOCLIM (Busby 1991), DOMAIN (Carpenter *et al*. 1993) and Maxent (Phillips *et al*. 2006). For example, Li *et al*. (2009) represented the global geographic distributions of three fruit flies and analysed the invasion of alien pests using three different SDMs. Furthermore, Yang *et al*. (2013) used the Maxent model to predict the potential distributions of medicinal plants in India.

These models have also been developed in geographical planning and design, as a means of managing visitors where they leave trails in winter based on the track location data of hikers (Coppes and Braunisch 2013), predicting winter recreation and sport zones from snow sport occurrence data obtained by one aeroplane (Braunisch *et al*. 2011), assessing the seasonal patterns of visitors using crowd-sourced photos (Walden-Schreiner *et al*. 2018), and mapping cultural services in a natural park from social media photographs (Clemente *et al*. 2019). In these studies, corresponding research entities were regarded as different species to predict their distribution areas. However, they only used the location information as occurrence records and did not mine specific semantics information. Therefore, based on the similarities between human emotions and species mentioned in Section 1, the SDM method may be applied and developed to map the distributions of emotions, combing concrete emotion attributes with location information.

3. Material and methods

3.1 Design

In order to clarify our methodology, a flowchart is presented in Figure 1 to describe our study. First, photos for the research period were collected from Flickr and filtered to include only those with geo-tagged and recognisable human faces. Raster representations at a global scale, for variables corresponding to the environmental factors (especially nature environments), were also prepared to meet the study standard. Second, human emotions were extracted and computed quantitatively based on state-of-the-art facial recognition and emotional computing tools. Third, various emotions in photos were mapped into corresponding grid units of a digital globe, and then the grid cells with sufficient emotional concentration were deemed 'occurred species' and extracted to form species occurrence samples. Finally, Maxent, the most successful species distribution model (Phillips *et al.*

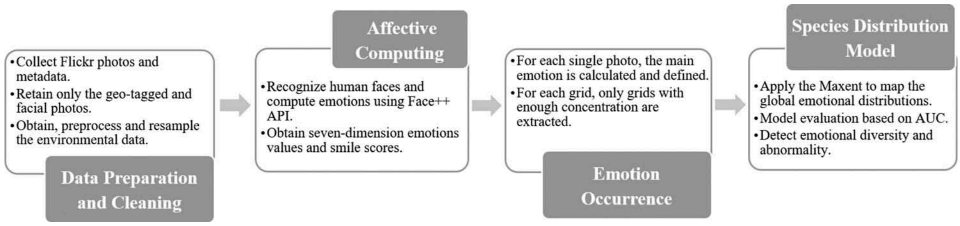

Figure 1. A flowchart representation of the different steps involved in the proposed framework.

2006), was applied to predict the *Emotional Habitat*, combining the occurrence samples of emotion with physical environmental factors. Furthermore, emotional diversity and abnormality were calculated and mapped based on previous outcomes. Note that in this study, we focus on the changes and differences of emotions across space not the time.

3.2 Data preparation and cleaning

The georeferenced social media photos were collected from the Yahoo platform named Flickr. This is a public social media platform where users can upload and share their photos spontaneously. The photo ID, user ID, geolocation information (latitude and longitude), original URL, uploading time and geotags of every photo are recorded automatically in the photo's metadata. These data provide exact identification of the location and some important environmental factors regarding where the user was when the photo was taken (Abdullah *et al*. 2015).

All photos taken from 2004 to 2014 on Flickr were downloaded with their metadata from the Yahoo Flickr platform (https://bit.ly/yfcc100md). The faces in these photos were recognised by a facial recognition tool available from the Face++ API (https://www.faceplusplus.com). Face++ API is a commercial cloud-computing AI technology and provides a publicly available cognitive service. The total accuracy of face detection by this tool was over 95%, which has been validated in previous research in (Bakhshi *et al*. 2014). From our datasets, we retained 13,128,398 photos with geo-tags and recognised human faces. Figure 2 presents the locations of all photos in the geographic space in the grid scale, with the concentration of colour indicating the number of photos in each grid cell. Considering the accessibility of environmental data and modelling efficiency in the computing platform, we chose a resolution (10 × 10 km) to represent the photo densities, which was consistent with environmental data.

Environmental data layers are used in modelling prediction procedures, consisting of important ecological factors and climatic features. Many environmental factors can influence local emotions. At different research scales, the main factors that affect human emotions and are applicable to this scale differ. For example, climatic variables likely affect emotional distributions at the global scale, while land cover features may influence emotional changes at the micro scale (Phillips *et al*. 2006).

Considering the scale, the data availability, and the model accuracy as explained in the discussion section below, this study chose the environmental factors shown in Table 1 (including 19 bioclimatic variables (Hijmans *et al*. 2005), air quality (Geddes *et al*. 2017, van Donkelaar *et al*. 2018), distance to water (Kummu *et al*. 2011) and the latitude variable

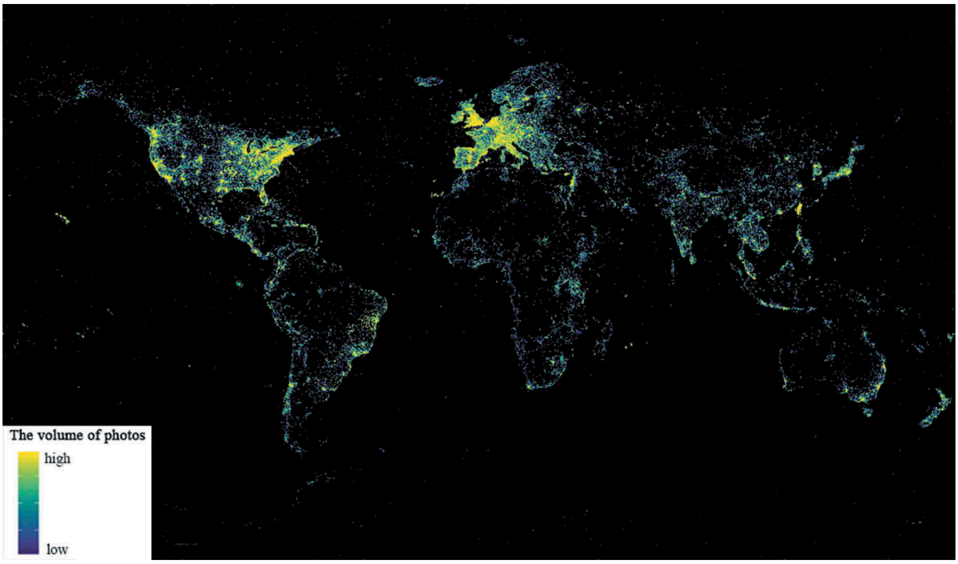

Figure 2. Global Flickr data distribution (2004–2014). The colour associated with each grid cell represents the volume of photos contained in it.

(Mersch *et al.* 1999). All environmental data are obtained from publicly available resources, which are detailed in the column 'references' in Table 1. Then, they were resampled to a resolution (10 $\times$ 10 km) using the nearest neighbour technique, yielding 23 layers with 4,320 $\times$ 2,160 grid cells.

3.3 Affective computing

We also used the Face++ Emotion API (https://www.faceplusplus.com/) to obtain and extract human emotions by submitting the photo meta-data URLs. The API detects facial emotions from photos using computer vision techniques and is said to perform well in several facial analysis competitions (Kang *et al.* 2019). Our output results mainly contained two aspects. First were the seven-dimensional emotion values, namely anger, disgust, fear, happiness, neutral, sadness and surprise. These likelihood scores (from 0 to 100) represent the confidence of the seven emotions, the sum of which is 100. The higher one of the dimensional scores, the more clearly the face expresses this kind of emotion. Second was the smile score (from 0 to 100). It was estimated by measuring the degree of lip and mouth contractions on faces. The smile score is 50 if the human mouth is neither rising nor drooping. Note that our study was based on each face in the photo dataset whether from an individual photo or a group photo. When several faces co-appear in one photo, different faces are regarded as different emotional records. This API has been validated for very high accuracy in emotional computing. The Pearson's correlation score between the results of the API and those of human labellers was 0.92 as noted in previous work (Singh *et al.* 2017). Thus, our emotional outputs extracted from the global Flickr photos can be deemed trustworthy.

Table 1. Environmental variables for the species distribution model.

Variable		Resolution	Description	Reference
Bioclimatic variables	Annual Mean Temperature Annual Precipitation Isothermality Max Temperature of Warmest Month Mean Diurnal Range Mean Temperature of Coldest Quarter Mean Temperature of Driest Quarter Mean Temperature of Warmest Quarter Mean Temperature of Wettest Quarter Min Temperature of Coldest Month Precipitation of Coldest Quarter Precipitation of Driest Month Precipitation of Driest Quarter Precipitation of Warmest Quarter Precipitation of Wettest Month Precipitation of Wettest Quarter Precipitation Seasonality Temperature Annual Range Temperature Seasonality	1 km	Interpolated climate surfaces for global land areas including monthly precipitation and temperature aggregated across a target temporal range of 1970–2000.	Hijmans *et al*. (2005)
Air quality variables	$PM_{2.5}$	0.01 degree	The annual concentrations of $PM_{2.5}$ from MODIS, MISR and SeaWiFS AOD across a target temporal range of 1998–2016.	van Donkelaar *et al*. (2018)
	NO_2	0.1 degree	The annual concentrations of NO_2 from GOME, SCIAMACHY and GOME-2 across a target temporal range of 1996–2012.	Geddes *et al*. (2017)
Distance to water		1 km	Global presentation of how close people live to freshwater features.	Kummu *et al*. (2011)
Latitude		10 km	Calculated the average latitude of each grid cell.	/

3.4 Emotion occurrence distribution

In this study, various human emotional expressions are regarded as different 'species'. These 'species' occupy their own 'niches' and 'habitats'. 'Niches' are unique environmental conditions but 'habitats' can overlap with each other in geographic space. With more than 13 million emotional samplings in photos distributing globally, only certain emotions with sufficient concentration in each of the 4,320 $\times$ 2,160 grid cells will be seen as 'occurred species'. In order to obtain the occurrence distribution data for the seven emotions, three steps were followed: (1) For each emotional record, the emotion with the highest probability to other emotions and its smile score meeting certain conditions was defined as the main emotion of this face, unless the emotion was 'happiness' or 'neutral'. For example, people were regarded as demonstrating the sadness emotion when the sadness dimensional value was maxima and the smile score was lower than 50 (i.e. the threshold of upper/lower lip); (2) If the emotion with the highest probability of the face was 'happiness' or 'neutral', then this probability had to be larger than 50% to define the main emotion, otherwise the photo was discarded for its weak emotional characteristics; (3) When mapping all filtered records with their main emotions into the 10 $\times$ 10 km grid cells, each of the seven emotions was averaged in each grid cell. However, only grid cells with at least 100 photos uploaded by at least 30 users across at least 50 days were regarded as effective occurrences of various human emotions to exclude the noise and spam information referring to (Doytsher *et al*. 2017). Each grid cell could have none, one or multiple main emotions, but cells with an averaged emotional probability smaller than 50% were removed. We hold onto one principle that each emotion is not affected by other emotions, just as living creatures co-exist in the same area. Lastly, these selected grid cells were converted into locational information as ultimate occurrence records. The statistics of the filtered photos and grid cells are shown in Table 2.

3.5 Species distribution model (Maxent)

We analysed the species occurrence data using a machine-learning approach based on the principle of maximum entropy, namely Maxent (http://biodiversityinformatics.amnh.org/open_source/maxent/). The Maxent model is considered one of the best methods to model species distribution when absence data are missing (Phillips *et al*. 2004). In our study, the absence of emotion observations cannot be interpreted as proof that emotion expressions do not exist in these places, hence Maxent was selected.

Maxent estimates probability distributions by adhering to the principle of closest to uniform using an iterative process based on the species' occurrences and environmental constraints (Phillips and Dudík 2008). It offers a greater probability to the presence sites and less to the remainder of the sites by involving fewer constraints but more choices, while remaining as close as possible to a principle of maximum entropy (Phillips *et al*. 2006). For our purposes, the unknown probability distribution π is over a finite set X of grid cells in the study area. The distribution π assigns a non-negative probability $\pi(x)$ to each cell x, and these probabilities sum to 1. The entropy of the approximation of π is defined as

$$H(\hat{\pi}) = -\sum_{x \in X} \hat{\pi}(x) \ln \hat{\pi}(x) \tag{1}$$

Thus, a distribution with higher entropy involves more choices. Each environmental feature is weighted with a coefficient that is iteratively changed until the probability maximises the likelihood of the species' occurrence. The ultimate habitat suitability in the output ranges from 0 (unsuitable habitat) to 1 (optimal habitat). The area under curve (AUC) in receiver operating characteristic (ROC) analyses is used to evaluate the model's

Table 2. Statistics of filtered photos and grid cells when obtaining occurrence distribution.

Seven emotions	Photo-level statistic	Grid cell-level statistic
Anger	628,797	502
Disgust	709,992	528
Fear	416,297	397
Happiness	3,652,935	1,355
Neutral	3,140,195	1,338
Sadness	789,623	606
Surprise	582,109	445

goodness-of-fit (Phillips *et al*. 2006). The ROC curve shows the performance of a classifier, whose output is independent of any particular choice of threshold. A corresponding AUC value exceeding 0.5 indicates that the model predicts better than random, while an AUC > 0.8 is generally considered good and acceptable.

We followed the recommendations regarding the parameter settings of previous research (Phillips and Dudík 2008, Clemente *et al*. 2019). Default settings were used for some Maxent parameters (Auto Features, Convergence threshold: 0.00001, Logistic output format), but with a few changes (Regularization Multiplier: 5, Maximum Iterations: 1000) to avoid over-fitting our train data. In the model, 80% of data were selected as a training set and the rest was used as a testing set to evaluate the prediction results.

To co-visualise the three essential emotional results (i.e. happy, sad and neutral) in one map, three outcomes were regarded as different 'bands' to implement composite bands commonly used within the remote sensing field. This was intended to produce a colour composite image by assigning three-band images to the RGB three primary colours, namely, colour synthesis. According to different needs, each band could be assigned a certain colour in the range of 0 ~ 255 grey value. In addition, to co-represent more than three kinds of distribution outcomes, the squared map was applied to visualise multi-dimensional emotional distributions in each original grid cell by mapping their relative proportion relationship into nine small grid cells after reducing the spatial resolution. A greater probability of one emotion may occupy two or more small grid cells compared with other emotions.

3.6 Emotional diversity and abnormality detection

Species diversity is a broad concept that describes the varying extent of biology in the field of ecology and represents the species richness in a given area. Similarly, 'emotion' species have also different diversity distributions around the world. Thus, we applied the Shannon-Wiener diversity index to measure emotional diversity as follows:

$$D = -\sum_{i=1}^{s} p_i \times \ln\ p_i \tag{2}$$

where p_i is the suitability probability of every emotion obtained from the Maxent and s is the number of emotional classes. The Shannon-Wiener diversity index is the most commonly used tool in species diversity surveys based on information theory (Whittaker 1972). If each sample belongs to totally different species in the place, the diversity index D for the corresponding location is greater. This index can represent the emotional richness of each grid cell where residents tend to express various emotions.

In addition to emotional diversity, we calculated and detected the girds with only one or two dominant emotional expressions and very high concentrations of emotions anomalously, namely emotional abnormality. First, the probabilities of six emotional distributions (excluding the neutral emotion) were standardised based on their means to form their emotional intensities in each grid cell. Then, the grid cells were extracted if their emotional intensities were larger than a relatedness threshold (i.e. the emotional intensities were in the 99% percentile of the global emotional intensity values), and defined as abnormal emotion distributions. The abundance of abnormal emotions in each grid cell was counted and visualised in the geographic space.

4. Results

4.1 Global happiness emotional distribution with SDM

Happiness represents the most intuitive human cognitive state and is consistent and universal across various cultures. Thus, we first only filtered and obtained happiness occurrence records in combination with the SDM to represent its global distribution and to test the effectiveness of our method.

Figure 3 shows the geographic distribution of happiness across the world. The AUC value of the trained species distribution model is 0.90 and is considered acceptable. Darker red represents happier regions. Generally, the east and west coasts of North America, Western Europe, the area between Brazil and Argentina, the eastern part of China, southern Japan and Australia's coastal areas are more likely to demonstrate happy emotions. Russia, the Sahara region and Antarctica do not present as much happiness, possibly due to their extremely cold or hot climates. Furthermore, we found that emotional distribution in the happiness dimension is highly correlated with the distribution of the world's population. The more people there are in one place, the more likely people express this emotion in this place even though more diverse emotions may appear there. Other dimensional emotions may show the same trend. These results illustrate that the species distribution model can simulate the relationship between human emotions and the physical environment, and provide predictions where sample data are missing. It is worth noting that low emotional probability does not necessarily mean that people in these locations are not as happy as counterparts in other areas, but that people may be less inclined to express explicit happiness. For the convenience of reading and explaining the result, high resolution version of the figure can be downloaded together with the source code as supplementary material.

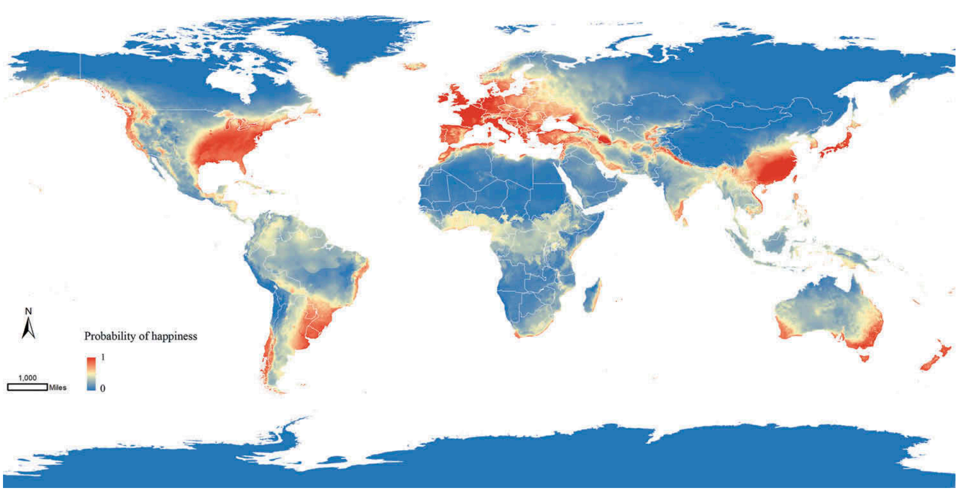

Figure 3. Prediction of the global geographic distribution of happiness emotion using the species distribution model Maxent.

4.2 Global geographic distributions of multi-dimensional emotions with SDM

After validating the effectiveness of our method using the single happiness emotion above, we ran the Maxent with filtered occurrence records of the six other emotions mentioned in Section 3.4 to obtain their global geographic distributions. These six model outputs (i.e. anger, disgust, fear, neutral, sadness and surprise) provided satisfactory results with the given set of training and test data. All six SDMs presented high accuracy, with their AUC values of 0.93, 0.92, 0.93, 0.90, 0.92 and 0.93, respectively.

Like every creature in an ecosystem, a place with a high co-occurrence probability of various human emotions has no conflicts. We found that the distributions of different emotions exhibit several similarities. Owing to the limitations of the article length, we do not plan to depict every emotional distribution separately. Rather, for better visualisation of their subtle differences, we first used colour synthesis to co-represent three emotional distributions: happiness, sadness, and neutral, and looked for interesting patterns (Figure 4). Based on the representation of an RGB image, pure red, green and blue colours stand for pure happiness, neutral and sadness emotions in each grid cell, respectively. When all three emotions co-exist in one cell, the cell becomes brighter. Obvious and subtle patterns exist in the colourful picture. First, major parts of North America are happier compared to in Europe, Asia and Africa, similar to the results in (Kang *et al*. 2018). Furthermore, a certain trend exists by which the western part of the United States (purer red colour) is happier than the east, even though the latter has greater happiness expression in Figure 3, consistent with the result using Twitter sentiments and expressions in (Doytsher *et al*. 2017). In addition, more happy emotions are expressed in coastal areas than inland, such as in Brazil and Chile in South America and Madagascar in Africa, although South Africa is less happy along the coast than inland. Happy emotion in North America, Europe and Asia gradually decrease according to their geographic locations from pure red to light blue to dark blue. Moreover, in Europe, an obvious regional differentiation of happy emotion distribution exists from west to east, gradually reducing in this direction.

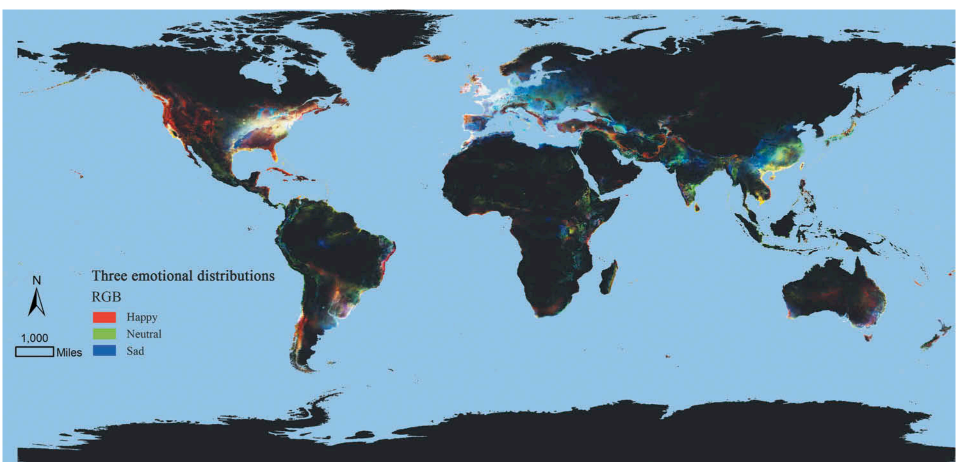

Figure 4. The co-visualisation of three emotional distributions obtained from SDM using colour synthesis. The saturation intensity of red, green and blue colours represents the probabilities of three human emotions: happiness, neutral and sadness.

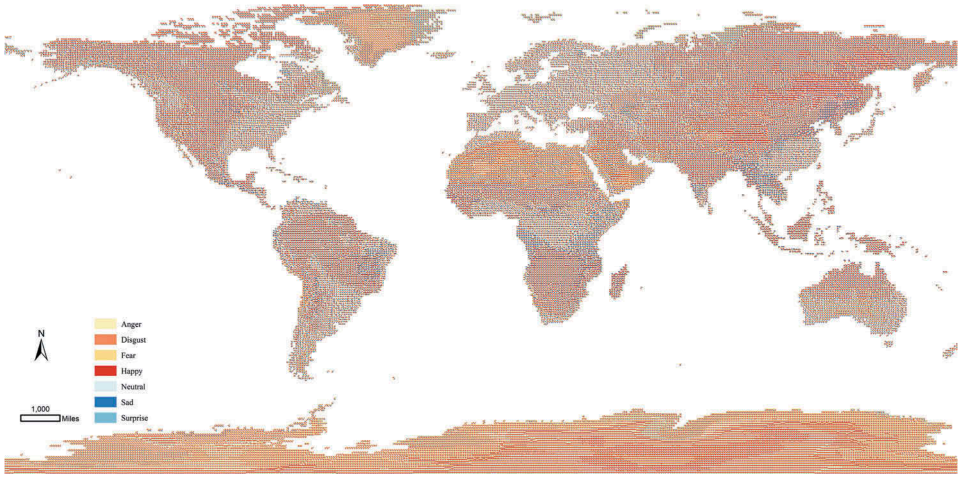

Figure 5. The co-visualisation of seven dimensional emotional distributions obtained from SDM by mapping their probability relationships into nine small grid cells of each original grid cell. Seven colours represent different emotions, specifically anger, disgust, fear, happiness, neutral, sadness and surprise.

In Figure 5, all seven emotional distributions are co-visualised in the pixelized map. Seven colours are filled into nine small grid cells to represent the relative probability proportions of each original grid cell. The obvious regularity of regional distribution differences exists. We found that the distributions of various emotions aggregate and cluster in geographic space. Some areas such as in Europe and the eastern United States have similar emotional distribution characteristics.

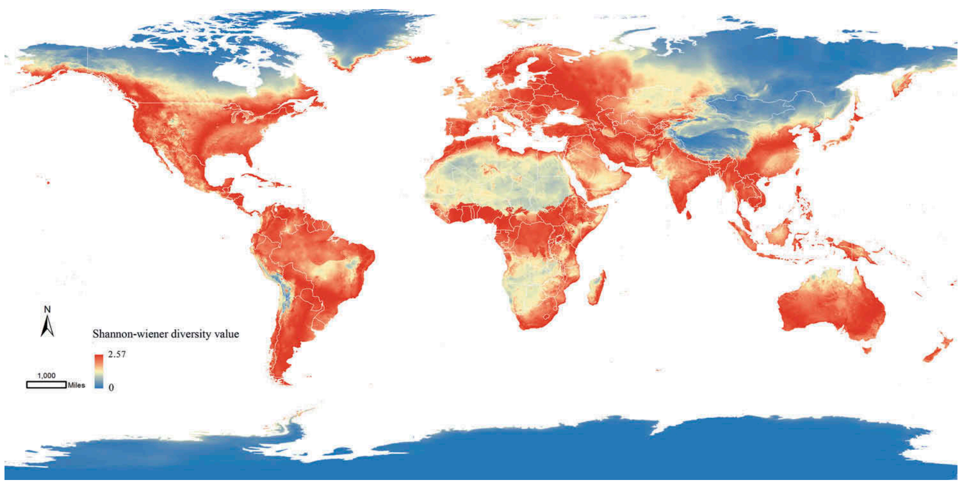

Figure 6. Global emotional diversity distribution using the Shannon-Wiener index. The higher the Shannon-Wiener index, the more the different emotions distribute in the area.

4.3 Visualisation of global emotional diversity and abnormality

Based on the Shannon-Wiener index mentioned in Section 3.6, the global emotional diversity from seven emotions was computed and mapped. The higher the Shannon-Wiener diversity index, the more the various emotions are rich and co-expressed. In Figure 6, most areas around the world present relatively high emotional diversities, while lower emotional richness reflecting relatively single human emotions is apparent in largely deserted places, such as most part of Greenland, Russia, the Tibetan Plateau in China, the Sahara and Antarctica, perhaps due to extreme climate and sparse populations.

Abnormal emotion distribution is identified and mapped in Figure 7, with four areas selected and zoomed-in. When only one specific emotional anomaly occurs, six different colours are employed to represent their types of emotions. If more emotional anomalies appear in the grid cell, light to dark grey colour is used to represent the abundance of emotional abnormality. Most abnormal areas are prone to co-appear as abundant

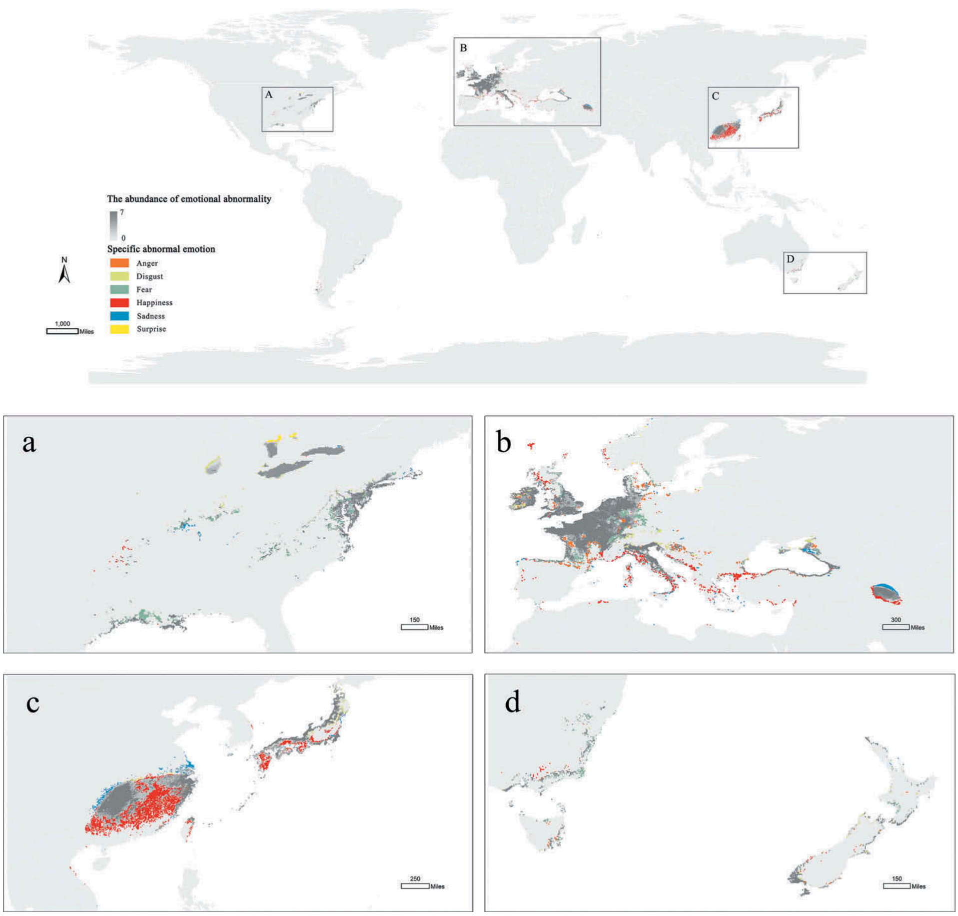

Figure 7. Global emotional abnormality distribution. The greyscale represents the abundance of emotional abnormality (from 0 to 6), and six colours show which kind of specific abnormal emotion (excluding neutral) respectively if the place only has one specific emotional anomaly. A-D are four sub-figures with four areas selected and zoomed-in.

abnormal emotion (grey) rather than as just one specific kind. Certain patterns emerge, such as abnormal happiness concentrating in south-eastern China, while single emotional abnormality often accumulates in coastal areas. The reasons behind these phenomena require further research.

5. Discussion

We have presented our method to map the global geographic distributions of various human emotions using affective computing and the species distribution model. Different emotions are regarded as different species to form their own 'habitats'. This method provides regional assessments of *Emotional Habitat* quantitively at the global scale, some of which have proved difficult to measure and predict.

As was the case with our emotional distribution results, several observed patterns are consistent with existing research outcomes, validating the effectiveness of our framework. For example, the majority of areas in North America are happier, while comparatively fewer faces are smiling in Europe, and racially Asians demonstrate a lower proclivity to express happiness in a picture than black and white people (Kang *et al*. 2018). Other similar results show that for entire areas in the United States, the west part is happier than the east (Mitchell *et al*. 2013). But Louisiana is the saddest state with a significant factor relative to the other states which is inconsistent with our findings. In addition, our results not only reflect the single emotion of happiness, but also provide a multi-dimensional depiction of emotion distribution. Several areas expressing various emotions are detected, and these distribution patterns are roughly similar in areas like the western United States and the western part of Europe, which are un-surprising and can be easily explained based on sociology and cultural discrepancy. We also found that people in places such as Russia tend to display lower emotional intensity in photos, while Europeans are more likely to show various feelings and emotions. Residents in an area where people often express one particular kind of emotion also tend to represent other emotions simultaneously, producing a positive synergy to enhance their emotional expressions.

It is desirable to next investigate more deeply into the explanations behind these observed emotional distributions and what factors may actually generate these distribution phenomena. Our results suggest that in more comfortable environments for human life, such as near water and in non-extreme climates, people tend to express more diverse emotions. However, the reasons for bringing about various human emotions in different environments are comprehensive and can be influenced by multiple internal/external and biological/social factors (Zhang *et al*. 2018). Furthermore, many of these influences are known to vary across personality and culture variables around the world. Thus, we do not expect that these distributions of human emotions can be explained for causal relationships. Rather, we hope to explore the reasons from the photo data we utilised.

The types of photos in the United States and Canada vary across urban and rural areas, where having a higher level of urbanization. From their photos, we could see greater well-being and colourful life. This may show that major parts of North America are happier compared with other areas. For photos uploaded in Russia, most were taken indoors, especially in churches with choirs, and their expressions were serious and calm. The happy emotion was also more frequently distributed in coastal areas than inland. In Brazil, people often uploaded their photos outdoors rather than indoors, such as enjoying the sunshine on the beach, taking part in carnivals or attending parties. The weather in these coastal areas is relatively comfortable and so people's facial expressions are open and enthusiastic. However, it can be seen from our photo dataset that coastal areas in South Africa are usually not places for relaxing but places for hiking and risking in the wild and inland areas are more developed and comfortable, which may explain the differences of results we produced. Furthermore, we noted that emotional diversity in Saharan areas is lower, with the photos suggesting that people there often use robes to cover their bodies and heads in order to protect themselves from the desert sun and thus they present less emotional expressions.

Some interesting abnormal emotion distributions can also be detected. For example, several abnormal sadness expressions exist at the centre of Figure 7(a). In these places, we found that numerous uploaded photos included babies and children crying and sleeping during daily life. This may be the reason behind their sadness and neutral values. These parents' behaviours may be related to local culture for early childhood development, especially in terms of cognitive stimulation, emotional arousal, verbal responsiveness and so on (LeVine *et al*. 1996). In Figure 7(b), people in the south-western coastal areas of the Black Sea uploaded many photos with sunshine and sea, and some even held the national flag to express their emotions. However, for photos in the north-eastern areas, people are often located indoors, with dim light rather than relaxing or travelling outdoors. These characteristics may cause different kinds of abnormal emotions in the north-east and south-west. In addition, abnormal happiness concentrates in south-eastern China in Figure 7(c). The Flickr photos there show tourist images and selfies with natural and cultural landscapes, expressing considerable joy and pleasure during the trip. Thus, by looking for the characteristics of the original photo data, some of the distribution patterns we observed can be explained.

Note that we used several physical environmental factors in our framework for the following reasons. First, with reference to existing research, human emotions can be influenced by natural environments (Tschakert *et al*. 2013, Graybill 2013); in some recent theory in the psychology field, exposure to nature has been regarded as an important factor behind human moods (Bowler *et al*. 2010, Svoray *et al*. 2018). Climate variables such as high solar radiation and high temperature have considerable impacts on people's psychological well-being and depression (Radua *et al*. 2010, Clayton *et al*. 2014), while precipitation also has effects on human mood (Yang *et al*. 2015). Second, the factors influencing human emotions at different study scales vary. At the global scale, natural environment variables are easier to obtain based on global uniform standards and are not affected by regional statistical differences. Other factors, such as regional openness and cultural facility accessibility may be not comparable in different regions and have less influence on emotional distribution at the global scale. Moreover, based on some pre-experiments, we found that some variables like population density and elevation had little contribution on emotional distribution in our model. Thus, we chose the final physical environmental factors in Table 1.

After fitting the Maxent model, the relationships between these physical environmental factors and the predicted emotions and their contributions can also be estimated. Because the objective of this study is not to analyse the associations but to map emotional distributions, we only list and discuss some important factors and their contributions to happiness species for the parsimony of this paper. We found that the air condition ($PM_{2.5}$

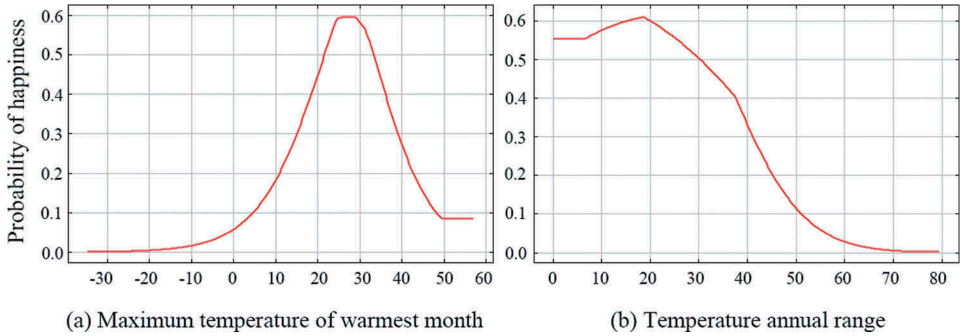

Figure 8. The relationships between the predicted probability of happiness and two environmental variables. (a) maximum temperature of warmest month and (b) temperature annual range.

and NO_2), the mean diurnal range and temperature annual range were regarded as the main factors influencing the distribution of happy emotion. Except for some factors like temperature annual range, the relationships between most factors and happy probability distribution were inverted U/V curves. Figure 8 presented how the predicted probability of happiness changed as two environmental variables were varied. We found that the environment with a moderate temperature had a greater probability of happy distribution (Figure 8(a)) and happy emotion was more possible to exist in the environment with small temperature change (Figure 8(b)) in our model.

Overall, our approach can predict the global geographic distributions of various emotions quantitatively through the incorporation of a species distribution model. This framework mines more adequate human perception information from facial expression in photos. Its outcomes further indicate that species distribution modelling approaches can be successfully adapted to assist in mapping emotional distribution. Moreover, it also overcomes numerous previous limitations mentioned in Section 1, such as not depicting in the same granularity and the difficulty of fitting distributions due to the presence-only sample. It enables an understanding of human emotion through combing methods from psychology, sociology and geographic information science with an ecological perspective that engages in diverse discipline interactions. This framework also confirms the theoretical correctness of the *Ecological Emotion* model proposed by Milton (2005) to dissolve the boundaries between multiple disciplines of emotional research, and enriches its content. Indeed, human emotion can be understood as a combination of biological, cultural and social phenomena, namely, an ecological mechanism. For future work, different common methods and indexes in the area of landscape ecology could also be used to analyse patterns in the produced maps, which may deepen the study of spatial heterogeneity in connection to the emotions.

Finally, this framework presents some challenges. First, some physical environment factors we used do not exactly coincide with the period of the Flickr data. Nevertheless, we believe that these emotional distributions around the world remain largely consistent over time. Second, when using images as a proxy for emotion, an inevitable bias towards genuine expression exists. The photos uploaded on the Internet tend to express more pleasant and happy faces. However, some research has shown that the emotions based on facial expressions do reflect users' real opinions and feelings at those places and provide new place-based information (Williams *et al*. 2008, Kang *et al*. 2019). The core motivation of our work is the development of an ecological model to predict emotion distribution based on a hypothesis that all bias factors exist and are consistent all over the world. Future work can combine different methods extracting human emotions into our framework in ways most appropriate for studies to correct bias and increase understanding of human emotions. Third, we mainly used annual average environmental factors to predict the emotional distributions and did not consider the changes in emotions over time. In this paper, we mainly focus on the differences among different places and assume how people express emotions are the same for a long time. Based on the effectiveness of our method at the global scale, further studies could be extended to a finer spatial scale combining more detailed and diverse environmental factors and considering their changes over time to guide urban planning.

6. Conclusion

In this study, a quantitative framework of mapping the geographic distribution of human emotion at the global scale using a species distribution model has been proposed and applied. To our knowledge, this framework is the first method to predict emotional distribution with a spatial model from an ecological perspective. Various human emotions have been treated as different species to form and predict their habitats without occurrence samples. State-of-the-art affective computing technology has been utilised to measure human emotions from facial expressions in user-generated photos uploaded on Flickr and then form emotional occurrences. Different spatial distributions of seven dimensional emotions have been explored across the world, and areas where people express diverse or abnormal emotions are detected. Some of the patterns confirmed our expectations, consistent with several outcomes in previous literature, whereas others were new and interesting. This framework offers new and useful insights to understand the relationships between human emotions and the physical environment. It also supports and enriches the research content of the ecological emotion model in emotional geography, which can be applied in different fields such as environmental psychology in the future.

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Data and codes availability statement

The codes that support the findings of the present study are available on Figshare at http://doi.org/10.6084/m9.figshare.11841372.

Disclosure statement

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