Probability-density risk-maps for tourism during emergencies

DYNAMIC RISK-MAPS FOR TOURISM DURING EMERGENCIES

1. Introduction

Tourism locations can be subject to emergencies that negatively affect tourism as people are afraid for their safety (Ritchie and Jiang 2019). Past studies have addressed the impact of risk perception on travel behavior and decision-making (e.g., Zenker and Kock 2020). They found that the majority of tourists is risk-adverse and over-estimates tourism-related risks (Wang et al. 2019). Thus, tourists change travel intentions and behavior to avoid risks, for instance, deferring travel (Wiliams and Balaz 2015). The COVID-19 pandemic provides a global example that is going on for several months now (Karabulut et al., 2020), with multi-billion losses.

This paper shows how to develop extremely detailed dynamic probability-density maps that represent an area's actual risk. They can help realign the risk perceptions of anyone visiting the region or residing there, but might apply in particular to tourists, as these maps allow to plot risk-levels around specific landmarks, like tourist attractions. Thus, they can contribute to containing the negative effects of an emergency by helping tourists and policy-makers identify which attractions are safe to visit and through which routes. As a consequence of implementing these maps, destinations can support tourism even during an emergency without compromising people's health and safety, rather than stopping tourisms tout-court. Such outcome could help both government and tourism managers (Ritchie & Jiang, 2019).

In the following, we show how to develop a probability-density risk-map of COVID-19 contagion for London. London was chosen as it is one of the main global destinations before the pandemic, with approximately 16.38 million overseas tourists in 2019 alone (Statista 2020). We map the main tourist attractions scattered across the city and each area's risk level, square-foot by square-foot. Then, we provide examples of how prospective tourists react to the map.

2. Dynamic probability-density risk-maps

Since individuals are dynamic entities, we need to model their behavior considering their (probable) movements in space, which impacts contact risk with infected/contagion.

First, we need to identify the mathematical function (f) characterizing our space (London). We call S the space (London), and r the attractions. To place the attractions (r) on the map of the space (S), we envision each attraction as a vector of two Real numbers, corresponding to its latitude and longitude. Thus:

$$f: S \to \mathbb{R};\ r \in S \mapsto f(r) \in \mathbb{R} \quad (1)$$

In this application, we map attractions with at least 15,000 reviews on TripAdvisor (at the time of data collection), which corresponds to the highest reviews rank. This led to the identification of 18 attractions, reported in Table 1.

Secondly, we define mathematically the probability of meeting an infected while visiting an attraction:

$$f(r) \geq 0\ \forall r \in S \text{ and } \iint_S f(r)\, dr = 1 \quad (2).$$

London (S) is organized into 33 local authority districts (boroughs) (Σ). Formally: $\Sigma \subseteq S$. Hence, the probability of meeting an infected in a specific borough is:

$$P(\Sigma) = \iint_\Sigma f(\boldsymbol{r})\, d\boldsymbol{r},$$

Also, $f(\boldsymbol{r}) = lim_{\Sigma \to \boldsymbol{r}} \frac{P(\Sigma)}{|\Sigma|}$, where $|\Sigma|$ is Lebesgue's measure of Σ (3).

Third, density correlates with contacting: the more infects in a place, the more likely contact becomes (Bertacchini et al., 2020). Although other factors besides density could play a role (e.g., open vs. closed spaces), density is considered the dominant factor to explain contagion probability (e.g., Castorina et al., 2020; Godio et al., 2020). Thus, the contact risk with an infect in borough Σ correlates with the number of infects in that borough and rises contagion risk.

Because the data about the number of infected in each of the 33 boroughs of London (Σ_1 to Σ_{33}) are cumulative and not homogeneous, we split the model for each borough. The total number of infects (T) in the 33 boroughs are:

$T = \{\Sigma_i, i = 1,2, \dots, n : \Sigma_i \subset \Sigma, \cup \Sigma_i = S \; and \; \Sigma_i \cap \Sigma_j = 0 \; if \; i \neq j\}$ (4).

The UK Government publishes daily data (D) regarding the number of COVID-19 contagions (m_i) in London's 33 boroughs: $D = \{(m_i, \Sigma_i), i = 1,2, \dots n\}$. Where $m_i \in \mathbb{N}$ is the number of infects in any given borough Σ_i. The association between each borough Σ_i, the number of infects m_i and the attractions $\boldsymbol{r}_{ij}$ in the borough is:

$\Sigma_i \mapsto \{\boldsymbol{r}_{ij} \in \Sigma_i | j = 1,2, \dots m_i\}$ (5).

Four, assuming a homogeneous distribution of the m_i infected persons of a borough, m_i can be assumed to be distributed randomly. Thus, m_i follows a normal bivariate distribution with mean in s_i, where s_i is the geo-localization associated with the specific borough Σ_i. Consequently, s_i represents a point in the borough and can be interpreted as the smallest space unit, like the square feet where one is standing. In other words, the map shows the probability density function of meeting an infected for the whole of London, borough by borough, and the smallest fraction inside each borough. This level of spatial detail is not only unprecedented, but also functional, as infected might move around (unless hospitalized or quarantined).

Five, the probability of contacting an infected while visiting a tourist attraction in a borough, can be evaluated through the probability function based on the Density Kernel Estimator Method (Botev et al. 2010). This is a non-parametric estimate for the dynamic probability-density function of a random variable in space (in this case, the probability of meeting an infected precisely there) and is usually employed for data smoothing on finite data samples. Applying the Density Kernel Estimator Method, we obtain:

$p_c(y) = \frac{1}{c\,h}\sum_{i=1}^{c} K\left(\frac{y-y_i}{h}\right)$ (6).

Where $Y = \{y_i, i = 1,2, \dots c: y_i \in S\}$ is the sets of all points (the infected) in space S, (London); $y \in S$ is the spatial variable K, smooth and symmetric, the kernel function for the probabilistic prediction model; h is the bandwidth parameter.

3. Results

3.1. The dynamic probability-density risk-map for London

We accessed the data published by the UK Government on the 1st of July 2020 (https://coronavirus.data.gov.uk). We used *Wolfram Mathematica* to develop the risk-map. The software allowed obtaining Y_i points in London, each representing an infected, distributed through the Montecarlo Method (Rubinstein and Kroese 2016) proportionally to the infects. The points (infects) were distributed in the 33 areas of 0.2 grades (one for each borough). A smaller grade value would have been mathematically possible yet meaningless in practice. A larger grade value would have led, instead, to a rougher approximation. The 33 areas representing the 33 London's boroughs were each centered on the geo-localization of s_i.

Table 1 reports the density probability for each Londoner attraction, with the normalized probability's corresponding value. The higher the number associated with an attraction, the higher the risk of meeting an infected there.

Attraction	**Normalized Risk value**	**Dynamic probability-density value**
National Gallery	1.504262	7.702237
Churchill War Rooms	1.492284	7.400447
St James's Park	1.489627	7.33479
British Museum	1.529626	8.373883

Victoria and Albert Museum	1.450535	6,421557
Tower Bridge	1.519243	8.093494
Tower of London	1.525181	8.252911
Westminster Abbey	1.489354	7.328068
Natural History Museum	1.445969	6.321143
Saint Paul's Cathedral	1.534369	8.504517
Royal Opera House	1.517524	8.047818
The Shard	1.515375	7.990988
London Eye	1.500887	7.616228
Hyde Park	1.464095	6.727383
House of Parliament	1.490322	7.351912
Borough Market	1.517162	8.038224
Sky Garden	1.531034	8.412491
Camden Market	1.533886	8.491138

Table 1. Density probability for the main London attractions

Figure 1 shows the probability-density function f (6), where the "peaks" and "valleys" represent - respectively- a higher and lower probability of meeting infects. The three axes represent the latitude, longitude, and probability of meeting an infect.

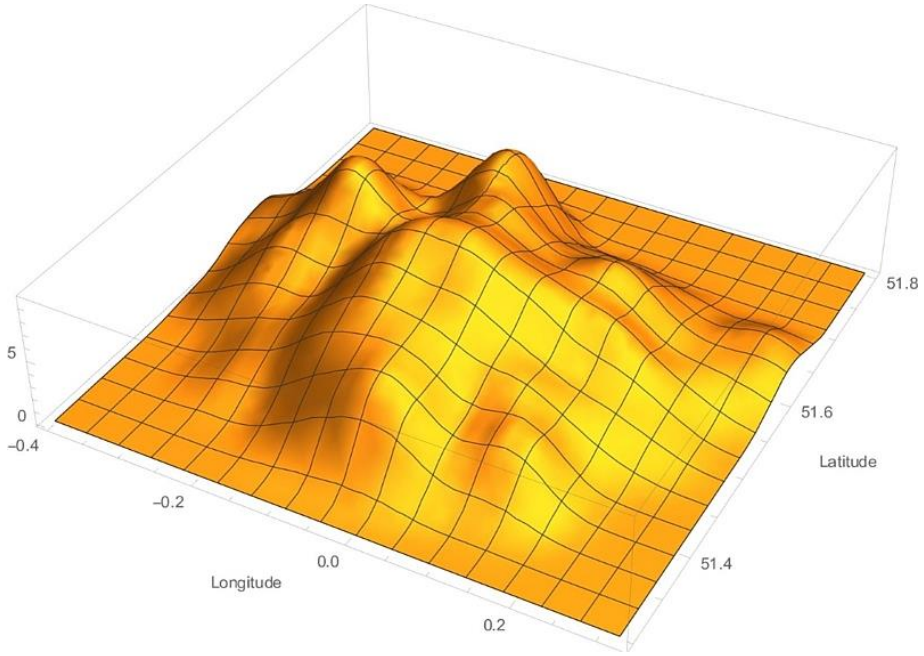
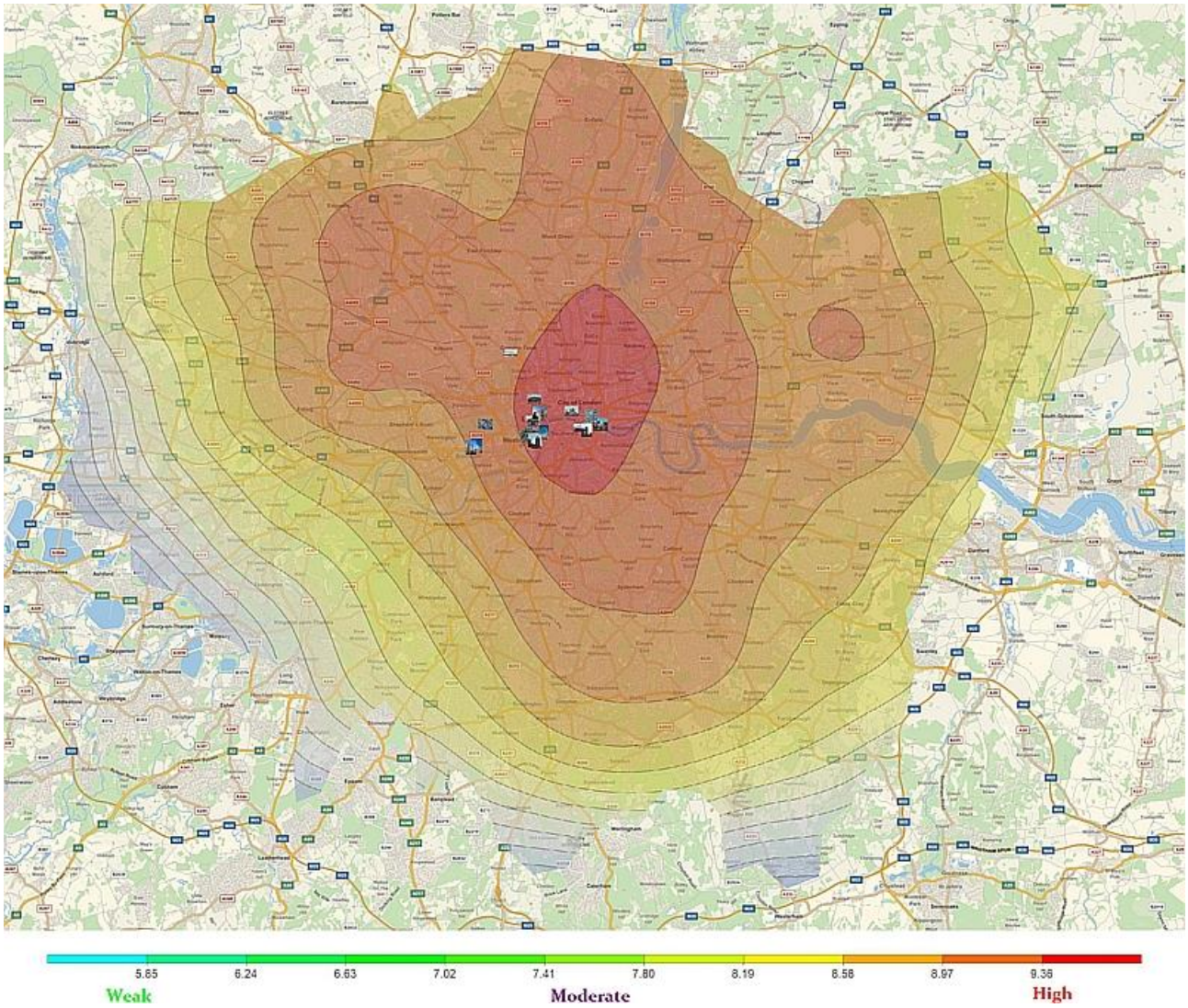


Figure 1: The dynamic probability-density function f.

Superimposing on Figure 1 the geographical map of London, we obtain the risk map in Figure 2. It can be zoomed in/out at will. Risk is shown with colors, from blue (lowest) to red (highest) instead of peaks.

Figure 2: London dynamic probability-density risk-map for COVID-19 contagion (July 2020).



3.2 Tourists' reaction to the risk-map

We run an online survey on 200 prospective Italian tourists (50% females, mean age = 25) from a Market Research company. Italy was the first country in Europe to lift travel restrictions, and about 2.50 million Italians yearly visit London, according to the UK National Tourism Agency.

Respondents saw either a normal geographical map or the risk map (randomized between-subjects). Both maps were 30cmx30cm (11x11 inches) with 300dpi resolution and could be explored (scrolling and zooming in/out). Respondents stated their perceived risk of traveling to London and travel intention in the near future. Then, they all saw the risk-map and stated their attitude toward the risk-map and perceived usefulness.

The risk map significantly lowered risk perception ($Mean_{normal\text{-}map} = 4.83$ vs. $Mean_{risk\text{-}map} = 3.48$; $F = 54.63(1, 191)$, $p < .001$) and heightened travel intention ($Mean_{normal\text{-}map} = 3.13$ vs. $Mean_{risk\text{-}map} = 4.20$; $F = 16.21(1, 191)$, $p < .001$). Perceived usefulness and attitude toward the map scored high (Usefulness: Mean = 5.10 St.Dev = 1.72, Median = 5.00; Attitude: Mean = 5.17, St.dev = 1.55, Median = 5.30).

In-depth, semi-structured interviews were run on with randomly extracted respondents with an introspective approach to explore reactions to the map, following McCracken (1988). They quickly converged after 20 interviews. Respondents revealed they opted for close rather than international destinations due to a lack of such information to minimize contagion risk. They stated the risk-map did not make them rule out traveling to London, and suggested them to avoid those attractions that were in boroughs at risk of contagion.

Overall, this example shows that the map influences respondents, supporting their decision-making.

4. Conclusion

This research provides a new procedure to map risk. The results lead to a high-resolution, extremely detailed map, where tourists' attractions are mapped together with the dynamic probability-density function of being exposed to health risks. These risk map apply to anyone visiting the region, and to residents, but are of particular interest for tourists, as they allow plotting risk-levels on a geographical map while highlighting specific landmarks, like tourist attractions (as shown in figure 2), and associate them with the punctual probability of contagion.

These maps can contribute to the research on COVID-19 effects on the tourism industry (Karabulut et al. 2020; Zenker and Kock 2020), and can also be applied to different risks (i.e., other diseases, terrorism, etc.). They show that, even where the overall risk is high, risk can change from area to area and from time to time. Thus, they allow enforcing safe routes for tourists, rather than shutting the whole area down. Especially for those areas with high income from tourism, this would greatly impact the local tourism industry's survival by avoiding tourism bans and closure of all attractions.

In a nutshell, the use of dynamic probability-density risk-maps can be framed in the broader topic of technology helping tourism destinations (Park, 2000), represent a predictive model to formulate new tourism scenarios, and answer recent calls for new tools to protect tourists against health risks (Wang et al. 2019; Wolff et al. 2019).

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