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Probability-density risk-maps for tourism during emergencies

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# 1 **DYNAMIC RISK-MAPS FOR TOURISM DURING EMERGENCIES**

2

## 3 **1. Introduction**

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

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

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

24 Then, we provide examples of how prospective tourists react to the map.

25

## 26 **2. Dynamic probability-density risk-maps**

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

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

$$33 \quad f: S \rightarrow \mathbb{R}; r \in S \mapsto f(r) \in \mathbb{R} \quad (1)$$

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

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

$$39 \quad f(r) \geq 0 \forall r \in S \text{ and } \iint_S f(r) dr = 1 \quad (2).$$

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

$$42 \quad P(\Sigma) = \iint_{\Sigma} f(r) dr,$$

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

44  
45 Third, density correlates with contacting: the more infects in a place, the more likely contact becomes  
46 (Bertacchini et al., 2020). Although other factors besides density could play a role (e.g., open vs.  
47 closed spaces), density is considered the dominant factor to explain contagion probability (e.g.,  
48 Castorina et al., 2020; Godio et al., 2020). Thus, the contact risk with an infect in borough  $\Sigma$  correlates  
49 with the number of infects in that borough and rises contagion risk.

50 Because the data about the number of infected in each of the 33 boroughs of London ( $\Sigma_1$  to  $\Sigma_{33}$ ) are  
51 cumulative and not homogeneous, we split the model for each borough. The total number of infects  
52 (T) in the 33 boroughs are:

$$53 T = \{\Sigma_i, i = 1, 2, \dots, n : \Sigma_i \subset \Sigma, \cup \Sigma_i = S \text{ and } \Sigma_i \cap \Sigma_j = 0 \text{ if } i \neq j\} (4).$$

54

55 The UK Government publishes daily data (D) regarding the number of COVID-19 contagions ( $m_i$ )  
56 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  
57 any given borough  $\Sigma_i$ . The association between each borough  $\Sigma_i$ , the number of infects  $m_i$  and the  
58 attractions  $r_{ij}$  in the borough is:

$$59 \Sigma_i \mapsto \{r_{ij} \in \Sigma_i | j = 1, 2, \dots, m_i\} (5).$$

60

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

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

75 
$$p_c(y) = \frac{1}{c h} \sum_{i=1}^c K\left(\frac{y-y_i}{h}\right) \quad (6).$$

76 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);  $y \in$   
 77  $S$  is the spatial variable  $K$ , smooth and symmetric, the kernel function for the probabilistic  
 78 prediction model;  $h$  is the bandwidth parameter.

79

80 **3. Results**

81

82 *3.1. The dynamic probability-density risk-map for London*

83 We accessed the data published by the UK Government on the 1st of July 2020  
 84 (<https://coronavirus.data.gov.uk>). We used *Wolfram Mathematica* to develop the risk-map. The  
 85 software allowed obtaining  $Y_i$  points in London, each representing an infected, distributed through  
 86 the Montecarlo Method (Rubinstein and Kroese 2016) proportionally to the infects. The points  
 87 (infects) were distributed in the 33 areas of 0.2 grades (one for each borough). A smaller grade  
 88 value would have been mathematically possible yet meaningless in practice. A larger grade value  
 89 would have led, instead, to a rougher approximation. The 33 areas representing the 33 London's  
 90 boroughs were each centered on the geo-localization of  $s_i$ .  
 91 Table 1 reports the density probability for each Londoner attraction, with the normalized  
 92 probability's corresponding value. The higher the number associated with an attraction, the higher  
 93 the risk of meeting an infected there.

94

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

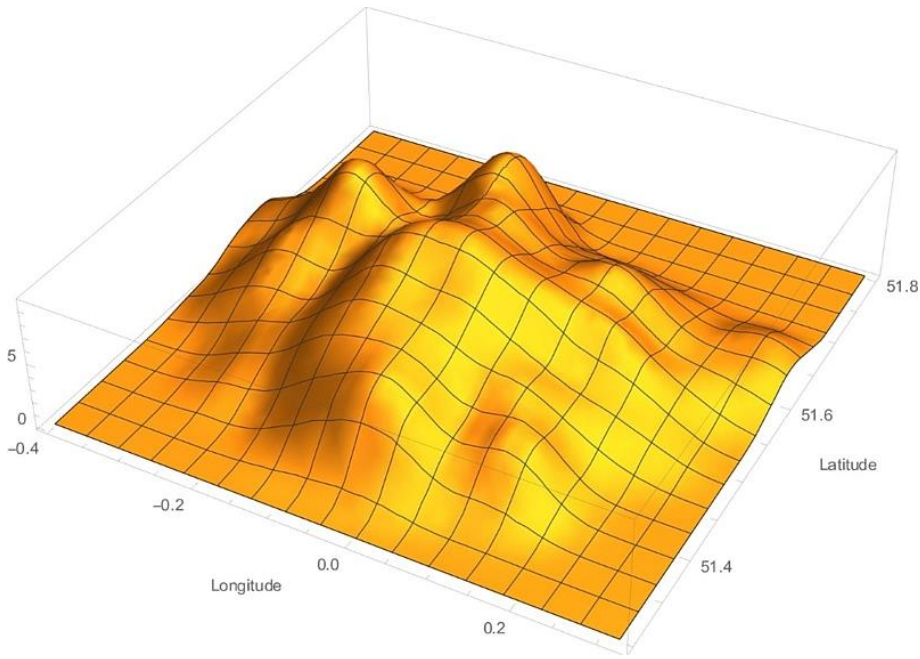
Victoria and Albert Museum	1.450535	6,421557
Tower Bridge	1.519243	8.093494
Tower of London	1.525181	8.252911
Westminster Abbey	1.489354	7.328068
Natural History Museum	1.445969	6.321143
Saint Paul's Cathedral	1.534369	8.504517
Royal Opera House	1.517524	8.047818
The Shard	1.515375	7.990988
London Eye	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

---

95 Table 1. Density probability for the main London attractions

96

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



100

101 Figure 1: The dynamic probability-density function  $f$ .

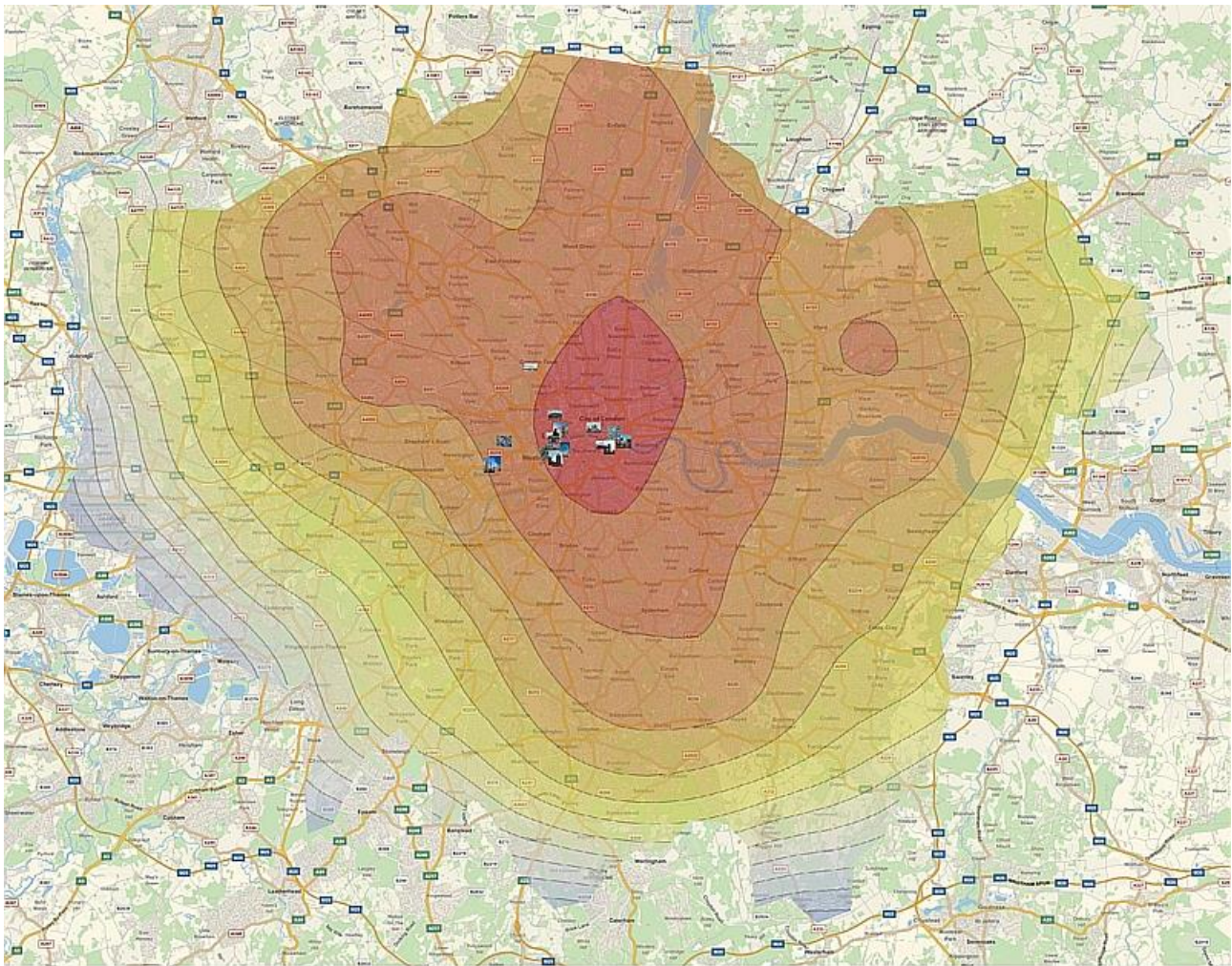
102

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

106

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





108

109

110 *3.2 Tourists' reaction to the risk-map*

111 We run an online survey on 200 prospective Italian tourists (50% females, mean age = 25) from a  
 112 Market Research company. Italy was the first country in Europe to lift travel restrictions, and about  
 113 2.50 million Italians yearly visit London, according to the UK National Tourism Agency.

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

119 The risk map significantly lowered risk perception ( $\text{Mean}_{\text{normal-map}} = 4.83$  vs.  $\text{Mean}_{\text{risk-map}} = 3.48$ ;  $F =$   
120  $54.63(1, 191)$ ,  $p < .001$ ) and heightened travel intention ( $\text{Mean}_{\text{normal-map}} = 3.13$  vs.  $\text{Mean}_{\text{risk-map}} = 4.20$ ;  
121  $F = 16.21(1, 191)$ ,  $p < .001$ ). Perceived usefulness and attitude toward the map scored high  
122 (Usefulness: Mean = 5.10 St.Dev = 1.72, Median = 5.00; Attitude: Mean = 5.17, St.dev = 1.55,  
123 Median = 5.30).

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

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

131

#### 132 **4. Conclusion**

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

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

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

149

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