doi.org/10.26398/asaproc.0017

Combining real-time spatial Delphi judgments and artificial intelligence for the development of future scenarios

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1. Introduction and theoretical framework

The exponential increase in complex and dystopian phenomena of environmental nature is rapidly spreading within territories, endangering the overall global population and ecosystem. Governments, local authorities, and scientists believe that if policies are not implemented immediately, dangerous effects could arise, jeopardizing human safety (Xu et al. 2020). In this context, proper planning becomes fundamental to counteract or prevent the effects of the ongoing climate impacts and those that could further increase in the future. Nevertheless, it cannot be adopted without a careful analysis of past and present information, aiming to avoid future threats. The complexity of the territorial structure is a multifaceted and intricate challenge that confronts planners and policymakers. It encompasses several interrelated factors, including geographical features, land-use patterns, infrastructure development, environmental considerations, socio-economic dynamics, and the aspirations of the community (Faludi, 2000). It follows, therefore, that specific approaches must be developed to achieve future objectives.

The study of futures remains an important aspect within the research line of *futures studies* (FS) with the aim of identifying hypothetical scenarios to act in the present to counteract or facilitate, respectively, future threats or opportunities (Kosow and Gaßner, 2008). In particular, scenarios can be considered as "*[…] an internally consistent view of what the future might turn out to be – not a forecast, but one possible future outcome*" (Porter, 1985). In other terms, the ultimate aim is not to predict a future event but to envision different futures to better manage present policies. In the spatial context, scenarios are predominantly crafted using spatial statistical models, which prove highly valuable in examining spatial data, detecting patterns, and making informed decisions regarding the studied phenomena. However, in FS, such models are often challenging to adopt for the following reasons: 1) *Data availability*: they require a substantial amount of data that is often either unavailable or only partially present for small areas. 2) *Prediction*: models produce *forecasts*, which have long been eschewed in the realm of *foresight* due to the inherent impossibility of attaining a singular view of the future. Over time, a transition occurred from the conventional approach of forecasting (which leaves no room for manoeuvring in changing the future) to embracing the exploration of multiple potential futures through the lens of foresight (Martin, 1995).

Among the many methods used to develop scenarios, *mixed-methods* remain a valid solution in order to have both a quantitative and qualitative perspective. Specifically, in this paper, we refer to the method proposed by Di Zio et al. (2017), namely the Real-Time Spatial Delphi (RTSD). RTSD is a customized approach combining the Real-Time Delphi (Gordon and Pease, 2006) and Spatial Delphi (Di Zio and Pacinelli, 2011), specifically designed to aid in foresight and decision-making. It leverages Geographic Information Systems (GIS) and multiple spatial technologies to facilitate expert communication and collaboration within a virtual environment with the final aim to obtain a convergence of opinions on the territory. In this process, experts' judgments become fundamental, both in combination with statistical models and for facilitating final decisions. RTSD in fact, solves one of the main problems of the traditional version of the Delphi method (Linstone and Turoff, 1975), namely the lack of spatial references in the process. In the scientific literature, RTSD found several applications in various research areas, including urban security and decorum (Di Zio et al. 2017), health, air quality, and energy (Castillo et al. 2017). Recently, Calleo et al. (2023), introduced for the first time the concept of "Delphi-based spatial scenarios" through an application in the climate change context, combining RTSD and the scenario method proposed by Bishop et al. (2007).

In this paper, the overall objective is to continue this line of research, providing innovation in the method by adopting a hybrid approach, combining RTSD and Artificial Intelligence (AI). In particular, since RTSD facilitates expert consensus-building on geographical locations, the final outputs are judgments expressed in the form of geographic coordinates (x, y), with a circle representing the consensus achieved—analogous to the interquartile range (IQR) of the classical Delphi procedure—and possible textual comments. However, the outputs produced are not in the form of scenarios and do not provide a narrative or a picture of the plausible future reality. With the rise of AI models, different methods can be used to visualize specific outputs starting from general inputs, including Generative Adversarial Networks (GANs) and Text-to-Image (T2I) models. Overall, this paper proposes to:

1. $\boldsymbol{O_1}$**:** combining Real-Time Spatial Delphi and Text-to-Image models to have a real vision, in the form of images, of the experts' consensus on the territory.
2. $\boldsymbol{O_2}$**:** exploring the capacity of images to foster consciousness and facilitate informed policy-making choices.
3. $\boldsymbol{O_3}$**:** developing a new hybrid method useful in the visioning phase of scenario planning (Bishop et al. 2007).

To showcase our novel method, we involve a panel of 26 experts in the process, asking to evaluate plausible impacts of climate change in 2050 for the city of Dublin, adopting a "Real-Time Geo-Spatial Consensus System (RT-GSCS – www.rtgscs.com, see Calleo et al. 2023). The judgments expressed by the experts in the form of geographic coordinates and textual comments within the consensus circle are implemented in a T2I tool (Adobe Firefly, www.firefly.adobe.com) in order to visualize the future impacts. By embracing this innovative approach, policymakers and experts can enhance the visualization of proposed policies, leading to a more effective assessment of their potential impacts with heightened accuracy.

2. Materials and methods

The method proposed in this paper combines RTSD and Text-to-Image models with the aim of developing future scenarios of possible impacts in 2050 for the city of Dublin and visualising renderings of possible threats in reality. To meet the research objective, we adopt the method proposed by Calleo et al. (2023) implementing it with an additional phase where AI is adopted (*visioning phase*).

The method is composed of the following phases:

1) *Framing*: where desk research is performed. Specifically, we develop the methodology of the study, acquiring spatial data available, and the area of interest in Dublin city. The city of Dublin is part of the SCORE H2020 EU project and is facing multiple challenges posed by coastal flooding in the upcoming years. For these reasons, we want to explore the climate impacts in a reasonable time horizon, identified as 2050.

2) *Scanning*: in this phase, a list of key drivers is extracted. Usually, in the traditional version of the Delphi method, this involves workshops and focus groups with experts, however, in our case, to speed up the procedure, we extract the main drivers from the project proposal since the drivers have been already refined by a group of researchers. In our study we identify six main hazards possibly affecting the future of Dublin in 2050: coastal flooding, land flooding, landslides, heatwave, storm surge, and coastal erosion. From these drivers, we can formulate the questions to be posed to our panel: $RQ1$: "Thinking about 2050, what area will be most at risk of flooding?" $RQ2$: "Thinking about 2050, what area will be most at risk of erosion?" $RQ3$: "Thinking about 2050, what area will

be most affected by extreme events?" Once we have a list of questions validated by the research team, in terms of transparency and clarity, we can proceed with the upload to the platform (RT-GSCS). The chosen panel adheres to the fundamental principles of the traditional Delphi method (Calleo and Pilla, 2023), considering the diverse range of expertise among the participating experts. In fact, we select a cohort of experts as part of two main categories: i) *Internal experts*: members of the project (SCORE H2020), including academics, stakeholders, and local authorities. ii) *External experts*: with a strong level of expertise and strong professional experience, including representatives from companies, local and governmental authorities, and NGO members. We contacted 12 internal experts and 50 external experts, and out of these $E = 26$ experts agreed to participate, including 6 internal and 20 externals.

3) *Forecasting*: in this phase, the Real-Time Spatial Delphi survey is performed. We sent a registration form to each panellist by email, including technical guidelines to access the platform. To pursue the objectives of this paper, we adopt RT-GSCS, a web-based open platform developed in 2023 (Calleo et al. 2023), to achieve a spatial convergence of opinions among panellists, with multiple tools including spatial analysis and real-time algorithms. Once the experts successfully register to the platform, the exercise can start. In this case, the experts can select the questions from a sidebar and answer by placing one or more points on the map. From this point, an automatic circle appears, moving, shrinking, and expanding in real time based on the anonymous responses from other experts. The experts have the option to justify their judgments at any time by providing comments. The statistical algorithm implemented in the platform is suggested by Di Zio and Pacinelli (2011) and aims to obtain convergence of opinions on the territory. Following this logic, spatial convergence is achieved by considering a geometric element identified by a circle C, the smallest among all the potential circles. In this case, C includes 50% of the N judgments – with $N \geq E$, since each expert can give more than one point for each question – (analogue of the IQR of the traditional Delphi). Once the experts place one or more points on the map, we have a vector of judgments $(n_1, n_2, \ldots, n_N)$ for each question, where each n_i is in the form of geographical coordinates (x, y). The main aim of the algorithm is to find a minimum area A_i of a circle C_i covering half of those points $A_i \supseteq T_{(N/2)}$, where $T_{(N/2)}$ denotes a set containing 50% of the N points. Nevertheless, since there are an infinite number of circles (C_i) that satisfy these conditions, we have the constraint that C_i must have its centre in one of the N points. Hence, for each question the algorithm determines a vector $A = A_1, A_2, A_3, \ldots, A_N$ where A_i represents the area of a circle containing 50% of the N points and centred at point n_i. Then, $min(A)$ – the smallest among all those circles – corresponds to the geo-consensus. With this approach, we have two types of final outcomes: i) *Geographical results*: the judgments represented in an interactive map. ii) *Non-geographical results*: the spatial and textual results. Geographical results offer an instant visualization, however, they do not depict the specific process of convergence. For this reason, the spatial Delphi (Di Zio and Pacinelli, 2011) involves the calculation of three main indicators to evaluate spatial data. $M_1 = FC(km^2)$ corresponds to the final circle (FC) area in km^2 useful for the identification of the portion of the territory identified. Nonetheless, this measure is absolute and does not consider the study area boundaries and the size of the initial circle. To address this challenge, we also consider as second indicator: $M_2 = 1 - \frac{FC}{S}$, calculated as the ratio between the final circle's area (FC) and the surface (S) of Dublin $(S = 117.8\ km^2)$. This indicator illustrates the level of geo-consensus, and the closer the measure is to 1, the smaller the consensus circle is relative to the surface. The third indicator, measures a dynamic process of the spatial convergence: $M_3 = \frac{FC}{IC} \cdot 100$, where IC is the initial circle area (set a priori as 50 km^2), and the higher the value (closer to 100%), the poorer the convergence of opinions; conversely, the closer it is to zero, the stronger the convergence. Since our process is in real-time, to end the exercise we must take into consideration a stopping criterion, identified in the literature as stability over time (von der Gracht, 2012). For this reason, in our case, we perform time series analysis, and we end the exercise when there is not a significant variation in the total distribution of the N points (usually under 5% of the

points).

4) *Visioning*: the novelty of the method is implemented in this phase. When we obtain the final results, we identify – for this preliminary study – the centre of the final circle area (A_i) of each scenario, but any other location inside the circle of consensus could be used. Currently, the point coordinates of A_i are imported into Google Street View (Google, n.d.) and the related real image of the examined area, is considered as input for our text-to-image model. In this instance, Adobe Firefly is employed as an artificial intelligence tool capable of generating images from textual inputs. This model adopts Generative Adversarial Networks (GANs) consisting of two neural networks: a Generator (G), responsible for generating images, and a Discriminator (D), which differentiates between real and counterfeit images through an adversarial process. At this stage, we bring the corresponding real image for each scenario into the model using the "Generative fill" tool. We then proceed to select the Regions of Interest (ROI), which represent specific areas of the image where the AI performs the generation process from the specific text input. Once the ROI has been identified we used a textual prompt to generate the modified image: for Sc.1 "*Generate a flooded road*", for Sc.2 "*Generate a coastal erosion*", for Sc.3 "*Generate extreme weather condition*" (for Sc. 3 given the general nature of the prompt, the ROI in the image is more expansive and encompassing). Ultimately, as a result, the T2I model generates a modified image based on the provided prompt. This capability can be exceptionally valuable for envisioning future events/scenarios and raising awareness among experts and the general public in order to develop efficient policies in the present.

3. Results and discussion

The study successfully addressed the research objectives, yielding 3 main spatial scenarios. It officially ran from November 1, 2022, to December 5, 2022, following a double stability check. For $RQ1$, 58 expert judgments with 13 comments were collected. $RQ2$ resulted in 54 judgments and 16 comments, while $RQ3$ recorded 40 points and 11 comments. The experts achieved a substantial reduction in the initial circles, exceeding 99% in all final results (referenced as M_2 in Tab. 1), indicating a remarkable level of convergence. In both Sc.1 and Sc.2, the initial circle underwent significant reduction, with M_2 values of 0.993 and 0.999, respectively. The initial circle of Sc.1 measured 8.24 km^2 and decreased to 0.77 km^2, while Sc.2 started at 3.25 km^2 and reduced to 0.15 km^2. In the case of Sc.3, the initial circle had a smaller size of 2.92 km^2, and it was ultimately reduced to 0.54 km^2, representing a reduction of 0.995, as indicated by M_2. In a conventional Delphi study, the Interquartile Range (IQR) is often used as a measure of consensus achieved when the IQR is less than 20% of the measurement scale employed. Likewise, in the Spatial Delphi method, consensus can be considered achieved when M_3 is less than or equal to 20%. In our study, the M_3 values of 9.34%, 4.61%, and 18.49% for the three research questions indicate that the experts achieved a high level of consensus for Sc.1 and Sc.2. However, for Sc.3 there was a slightly lower level of consensus due to the presence of multiple clusters on the territory.

Table 1. Measures of spatial consensus

Scenario	S (km^2)	IC (km^2)	FC (km^2) M_1	M_2	M_3	N
Sc.1	117.8	8.24	0.77	0.993	9.34%	58
Sc.2	117.8	3.25	0.15	0.999	4.61%	54
Sc.3	117.8	2.92	0.54	0.995	18.49%	50

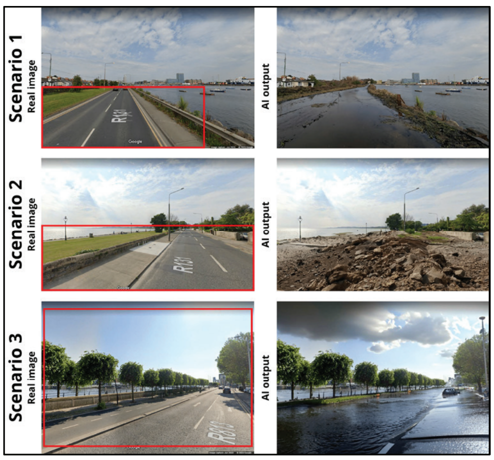
As stated in Section 2, while consensus is an important aspect when determining the survey's stopping criterion, it is not the sole factor, and stability also holds significance. Overall, Sc.1 experienced multiple changes before stabilizing from the 18th to the 20th day. Nevertheless, after validation, three additional changes occurred, highlighting the contentious flooding issue in the Dublin area and uncertainty regarding appropriate solutions. Sc.2 demonstrated the strongest consensus, remaining stable from the 10th day and only undergoing two changes during validation, signifying agreement on future spatial erosion dynamics. Sc.3 exhibited significant changes in the circle's radius within the first 15 days, reflecting debates about potential extreme event scenarios but stabilizing after the 18th day. Once we illustrated the dynamic process of convergence, spatial analysis is performed adopting ArcGIS PRO (Fig. 1).

Figure 1. Delphi-based spatial scenarios

Sc.1 depicts that by 2050, the central part of Dublin city, between the banks of the River Liffey, faces the highest threat of flooding. Experts are concerned about potential harm to buildings, infrastructure, essential services, the environment, and even loss of life. Moving to Sc.2, eastern coastal regions of Dublin are identified as most susceptible to erosion by 2050. Coastal erosion here could lead to the loss of valuable real estate, infrastructure, risks to public safety due to unstable cliffs, and negative impacts on tourism and fishing. Regarding Sc.3, the central area of Dublin is seen as most likely to be impacted by various extreme events like storms, floods, and heat waves. Following the experts' comments, consequences include damage to buildings, infrastructure, disruptions to daily life, threats to public safety, strain on emergency services, healthcare, and environmental implications affecting local ecosystems and habitats.

The results provide immediate insights from the experts' judgments; however, they are spatial representations and may not fully convey the reality and magnitude of the threat. Policy makers and citizens might not be aware of the potential implications of future threats. To address this, we generated plausible visual scenarios adopting T2I models, with the aim of providing a clearer understanding of the possible outcomes.

Figure 2. Results from the Text-to-Image model



The generated images are highly significant and offer a clear and well-defined representation of potential future scenarios. In Sc.1, the ROI is replaced by a visually suggestive depiction of a flooded road. Likewise, for Sc.2, we illustrate the erosion phenomena affecting the road. Lastly, Sc.3 demonstrates the impact of extreme events, resulting in the flooding of the road and disrupting transportation.

4. Conclusions and future works

This paper proposed a novel hybrid method combining Real-Time Spatial Delphi and Artificial Intelligence to represent experts' judgments. We employed T2I models to generate plausible visual scenarios, providing clearer insights into potential future threats. These visually suggestive representations offer valuable information to policy makers and citizens, helping them understand the magnitude and implications of the identified threats. However, it is essential to emphasize that these images are hypothetical visions designed to raise awareness among citizens and policymakers, encouraging them to take appropriate actions in the present. In future works, this method can be used to generate realistic images of concrete policies to be adopted in the present in order to facilitate the work of policymakers.

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