ICONHIC2022
3rd International Conference on Natural Hazards & Infrastructure
5-7 July 2022, Athens, Greece

A baseline approach to downscaling Euro-CORDEX data for wind hazard assessment of the Egnatia Odos highway

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ABSTRACT

The wind hazard is assessed for the Egnatia Odos highway in Greece by considering Climate Change effects via the Euro-CORDEX future climatic projections. The aim is to derive spatially correlated region-wide wind fields for a stochastic event set of thousands of storm realizations that are suitable for risk and resilience assessment of the entire highway network. The coarse spatial and temporal resolutions of the Euro-CORDEX wind projections prohibit their use as a direct input in weather-related risk and resilience assessment of highway structures that may measure down to a few meters in size and require at most 10-min average wind speeds. To improve the temporal scale resolution, we leverage machine learning tools and continuous measurements from National weather stations to generate composite “Frankenstein” days comprising 144 jigsaw pieces of actually measured 10-min wind time-histories that are scaled and matched together to form a continuous daily record. These point-estimates, valid only at the locations of the weather stations, are expanded spatially by employing high-fidelity Computational Fluid Dynamic simulations that take into account the topographic complexity of the site to simulate turbulent wind flows, thus generating spatially correlated wind fields of 10-min average wind speeds. These allow estimating load distribution and risk on (i) an event-by-event basis and (ii) in the long-term for an ensemble of spatially-distributed highway assets that are vulnerable to wind actions, such as signpost bridges and power network pylons.

Keywords: wind hazard assessment, wind fields, Climate Change, road infrastructure

INTRODUCTION

Climate and weather models/data come with a spatial and temporal resolution that may refer to kilometers and days, respectively. On the other end, civil engineering materials, structures and infrastructure are characterized at the level of centimeters or meters, while they dynamically respond to load time-histories discretized to fractions of a second. Bridging these two different scales is essential for projecting the effects of weather and climate on any individual structure. Further challenges are posed by building ensembles and interconnected infrastructure networks that also require cotemporaneous spatially-correlated fields of weather data, e.g., assess losses and downtime across a complex system swept by a single weather episode/event. This is the case of assessing a highway Road Infrastructure (RI) comprising signposts, lighting poles, toll booths, antennas and powerlines all under the same passing winter storm that might subject towers, steel members, conductors etc. to beyond-design-level wind speeds. Smart solutions can and have been implemented to tackle the lack of resolution per each individual type of structure and deterioration/failure mechanism. For example, annual maxima are used to capture extreme load effects (EN 1991, 2005), while characteristic years may be used to simulate the lifecycle deterioration under cumulative ageing mechanisms. Still, each such shortcut carries its own idiosyncrasies that do not necessarily lend to a consistent approach over an extended system, where multiple simultaneous failures can have a disproportionally large impact. What we instead propose is having a common basis with uncompromising spatiotemporal correlation of wind speed, suitable for any assessment purpose.

In the context of the PANOPTIS project (2018), the effects of future climate on interconnected highway assets are assessed by taking advantage of coarse wind projections provided by the Euro-CORDEX (EC) database (Jacob et al, 2014), typically at a 12.5x12.5km grid per each day until year 2100, which are transformed to correlated 10-min time-histories at each geolocated point of interest. To do so, we employ historical weather station (WS) measurements and spatially correlated weather intensity measure fields (WIMFs) that provide cotemporaneous wind speed and direction values at all locations of interest. The obtained 10-min WIMFs that are derived from the 10-min time-histories are not expected to deliver a better short-term or more localized forecast/assessment, but they can bridge the resolution gap to provide consistent time-varying fields of weather parameters at a scale that is suitable for building-level engineering work, while they respect the long-term and large-scale statistical trends identified from existing data. The proposed methodology for generating the Frankenstein 10-mins and WIMFs is employed for assessing the wind risk for the Metsovo-Panagia segment of Egnatia Odos in Greece.

FRAMEWORK FOR DOWNSCALING THE EURO-CORDEX WIND PROJECTIONS

Euro-CORDEX provides projections of multiple climatic parameters in the future that rely upon alternative Climate Change (CC) scenarios. The CC scenarios are determined based on the greenhouse gas emissions of the Representative Concentration Pathways (Moss et al, 2010). For each emission scenario, multiple realizations of the climatic parameters are derived, each one coming from a different combination of general circulation model and regional climate model, with the former providing data in relatively coarse spatiotemporal resolutions and the latter employed to further downscale them. The resulting spatial resolution of most EC models is 0.11° or approximately 12.5km and the typical temporal resolution is one day. In other words, each day within, say, years 2000 to 2100, henceforth termed “EC-day” is represented by a single estimate of each weather parameter at each 12.5x12.5km cell, henceforth termed “EC-cell”. An example of precipitation, wind speed and direction projections obtained for an arbitrary EC-day for the Metsovo-Panagia segment of Egnatia Odos is shown in Fig. 1. In our case, among all EC parameters we are interested in the daily maximum wind speed and average wind direction that is computed via the eastward and northward near-surface wind speeds provided by EC.

The coarse spatial and temporal resolution of the EC data do not allow using them as a direct input for wind risk and resilience assessment of the highway; thus both resolutions need to be downscaled. They are downscaled on a 10-min basis by taking advantage of historical measurements of the WS that fall within the EC-cells of interest. For each EC-day, machine learning is employed to identify the three closest historically measured WS days that better match the daily EC target parameters. Having found these WS-days, their 10-min values are combined to generate an artificial timeseries for the entire day, termed Frankenstein day (FS-day) by its Mary-Shelley-esque virtue of being composed of initially mismatching parts of actual WS-days fitted together to recreate plausible high-detail characteristics of an EC-day. This synthetic, realistic but not real, day consists of 144 values of 10-min wind speed and direction, which retain as best as possible the correlation of WS measurements in time and space. This process allows obtaining future wind projections with a 10-min resolution at the locations of the WS for which the corresponding measurements are available.

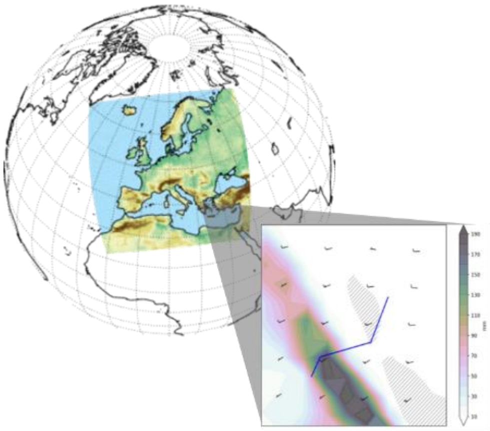


Figure 1. *Example of Euro-CORDEX data for a part of the Egnatia highway (solid blue line) in Greece on an arbitrary day. The shading of the lower right figure shows daily precipitation values, the hatch is used for areas where the wind speed is higher than 15m/s, and the barbs show the mean wind direction. The upper left figure is adopted from https://www.euro-cordex.net/.*

This point-specific Frankenstein dataset can be expanded to encompass the 12.5x12.5km EC-cell if the spatial pattern of wind is known in order to generate 10-min spatially and temporally correlated Frankenstein WIMFs. To achieve so, spatially correlated wind speed and direction WIMFs are employed that are the product of site-specific simulations. They provide 10-min spatially correlated values for a grid of points and allow expanding the suite of local weather parameters to all locations of interest within the WIMF grid.

APPLICATION IN THE CASE-STUDY

The proposed methodology is employed within the PANOPTIS project for assessing the weather-related hazard for the Metsovo-Panagia segment of the Egnatia Odos highway in Greece (Fig. 2). The highway has been constructed in a high-altitude environment and comprises multiple RI assets such as long bridges, tunnels and steep slopes, as well as many non-RI assets that enhance the functionality of the highway, e.g., steel signpost bridges, toll stations, utility poles providing power to the highway etc. Most of the non-RI assets are vulnerable to the weather-related hazard and specifically to high winds that might load the structures beyond their capacity even leading to collapse. For this reason, it is of significant importance to assess the wind hazard on a 10-min temporal resolution that allows linking it to the structural analysis results that are typically provided using the 10-min wind speed at 10m height, u_{10}, as the intensity measure.

For simplicity in our case only the Metsovo WS (Fig. 2) is considered in the analysis. It is installed at 1240m altitude with its anemometer being placed at 2m height, and provides 10-min wind speed and direction measurements. To ensure compatibility with the structural analysis, the wind speed values of the WS, u_h, are converted from the anemometer height, h, to a 10m height via a power-law profile:

$$(u_h/u_{10}) = (h/10)^a \tag{1}$$

where u_{10} is the wind speed at 10m height and a is a dimensionless parameter with a typical value of 0.2 for onshore areas (IEC 61400-1, 2005).

For illustrative purposes the EC data are spatially and temporally downscaled for a single EC model, i.e., the RCA4-MPI-RCP2.6 (Jacob et al. 2014), and on an arbitrary EC-day. The 12.5x12.5km EC-cells for the given model are shown in Fig. 3, where the entire demo site and the Metsovo WS fall within one cell. The maximum daily wind speed is u_{max} = 4.94m/s, while the average wind direction, θ, is computed from the daily average northward and eastward wind components on the given day. Assuming that enough WS-days are available, the idea is to match the given EC-day to past WS-days already measured. Finding the WS-day that better represents the EC-daily values is a challenge that requires bridging their different spatial and temporal resolutions. The

EC data is global, i.e., EC-cell-level and daily while the WS data is local (grid point) and discretized to 10-min intervals. The first task is to characterize each WS day at EC-cell level and daily values. Theoretically, we should be doing this regardless of the EC-day data by simply transforming the WS wind speeds and directions to global and daily levels. Still, this mapping is not necessarily one-to-one as the same local and short-period wind speeds and directions can mean potentially different things at nearby locations within the cell, based on e.g., the prevailing high-altitude wind direction. In other words, this transformation differs depending on the average daily wind direction of the EC model, which acts like a “hidden” parameter that is not be detectable at the WS level.

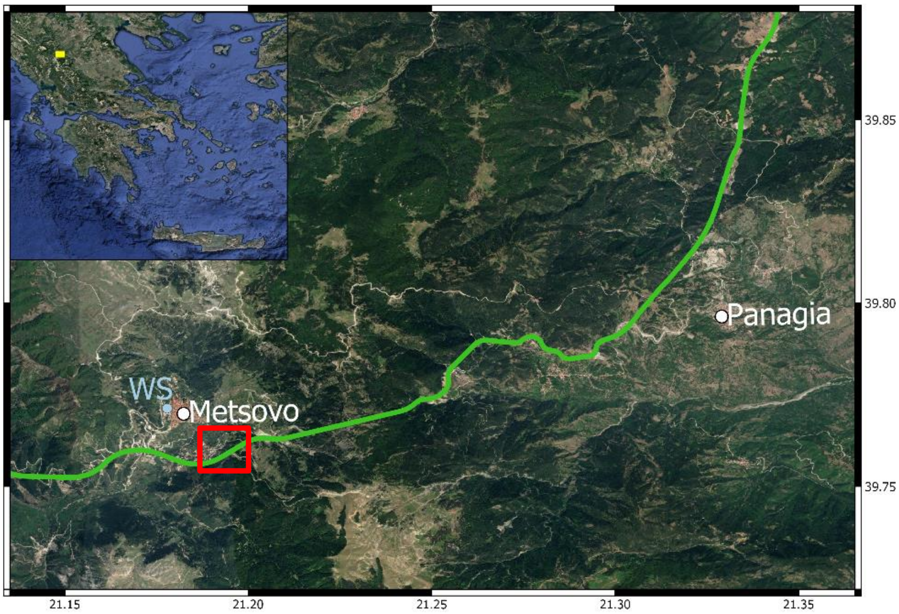


Figure 2. *Metsovo-Panagia segment of the Egnatia Odos in Greece showing also the location of the Metsovo weather station (WS) and the Metsovo valley indicated by the red rectangle.*

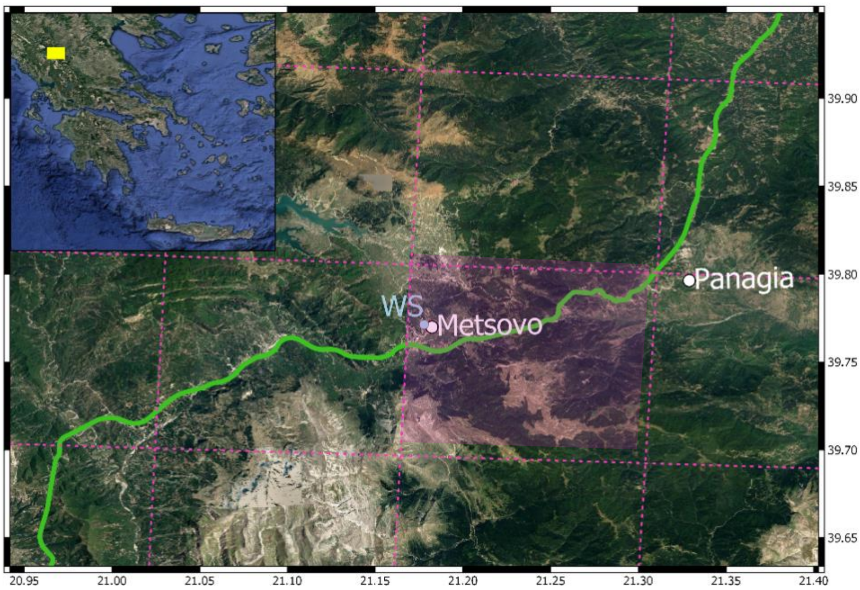


Figure 3. *Boundaries of the RCA4-MPI-RCP2.6 Euro-CORDEX model at the Metsovo site shown in dashed magenta lines. The entire demo site falls within the highlighted Euro-CORDEX cell.*

To achieve mapping of the WS and EC-data, spatially distributed WIMFs are employed that allow linking point WS estimates to global EC-cell level values. In our case the WIMFs are computed from high-resolution Large-Eddy Simulations (LES) via the PALM model (Maronga et al, 2019, Raasch & Schröter 2001, Hellsten et al, 2017), which take into account the topographic complexity of the site to simulate wind turbulent flows. They provide spatially correlated wind time-histories in 3D space that are computed for a given magnitude and direction of the prevailing, i.e., high-altitude wind direction under isothermal conditions. An example of the vertical section of a wind field that is generated for North prevailing wind direction around the Metsovo valley in Greece (see Fig. 2) is presented in Fig. 4. Typically, such simulations should be repeated for multiple wind profiles of increasing intensity but this would require considerable computational effort. For this reason, the LES wind time-series are assumed to be linearly scalable to allow matching any level of wind intensity of interest. Still, such scaling does not account for increases in the roughness layer due to the increased wind speed, thus, for large scale factors the corresponding wind gusts may be underestimated.

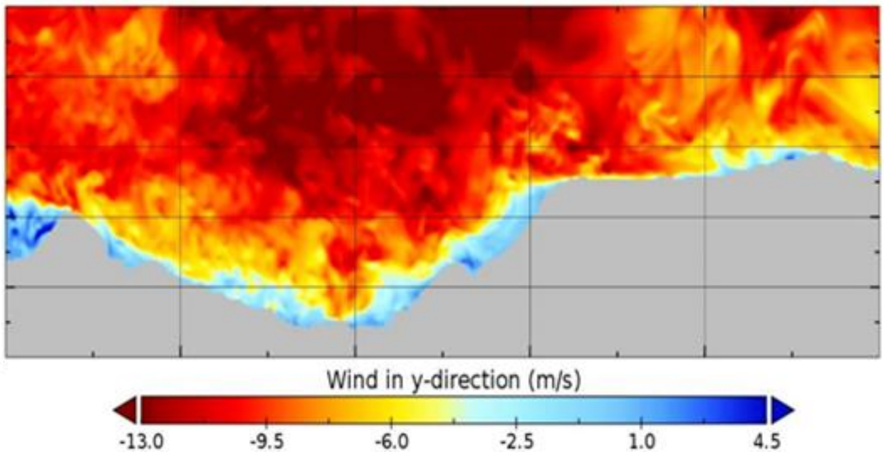
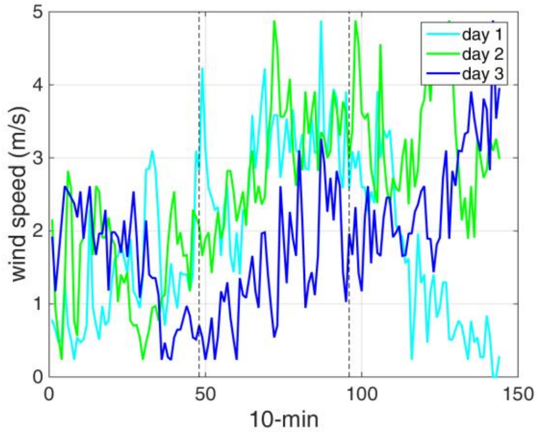


Figure 4. *Vertical section of the turbulent wind velocity distribution computed via the LES simulations for North prevailing wind at the Metsovo Bridge valley.*

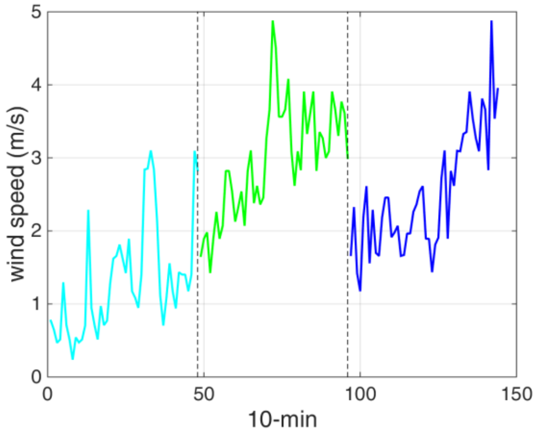
The LES simulations are performed for 12 prevailing wind directions, each being representative of a ±15° sector. They provide 1-hour wind time series that are converted to six alternative 10-min realizations of wind speed and wind direction WIMFs at all simulation sites. These spatially distributed WIMFs are employed for mapping the WS and EC-data to generate the Frankenstein days and WIMFs. As a first step, the most appropriate LES dataset is determined for the target EC-day. Since the link between the EC and LES data is not straightforward, it is assumed that in large-scale analysis, such as the one performed by EC, the adopted digital elevation model is often coarse and does not allow accounting for local effects, such as mountain-induced turbulence. For this reason, the EC daily wind direction is assumed to match the prevailing wind direction of the LES simulations, considered to be constant within each day. This allows obtaining localized 10-min wind speed information at all simulation sites for each EC-day and determining the average EC-cell-level wind speeds by the following steps:

- The LES WIMFs that are computed for the prevailing wind direction implied by the EC-daily wind direction are selected.
- For each WS day:
  - For each 10-min of the WS data, one out of the six 10-min WIMFs of the selected LES is randomly chosen and scaled to match the 10-min wind speed measured by the WS. The average EC-cell level wind speed is determined when all LES simulation sites within the EC-cell are considered via the scaled WIMF.
  - The maximum daily EC-cell level wind speed is computed by considering all 10-mins of the WS day. This EC-cell level daily maximum wind speed of the WS day bridges the different temporal and spatial scales of EC and WS data.

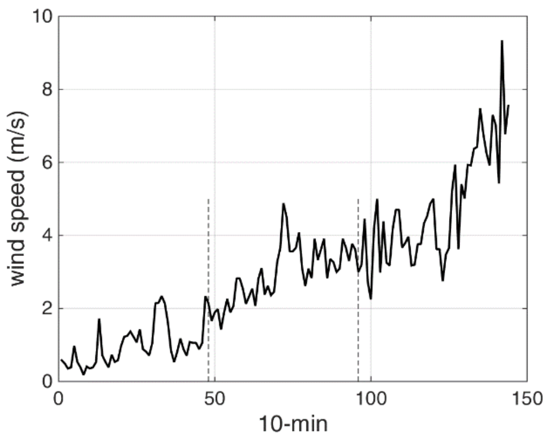
Still, mapping the different temporal and spatial scales for wind direction by converting the local WS to global EC-cell level values is not an easy task. For this reason, the inverse process is followed and the wind direction distribution is determined at the WS location for the EC-target day. To achieve so, the wind rose at the WS location is determined from the selected LES dataset of the given EC-day, and assumed to be representative of the local wind direction statistics of the EC-day. For the WS days, the wind roses are determined based on the 10-min wind speed and direction measurements. Having determined the wind roses at the locations of the WS and the EC-cell, and the maximum EC-cell-level daily wind speeds for the sample WS and the target EC-days, the WS day that better matches the target EC-values needs to be found. In a perfect setting, one would have as many observations as needed to match any EC-day prediction. In practice the observed WS samples are limited thus there is not enough data to perfectly reproduce a 24hrs timeseries to match any given EC-day, thus the *k*NN algorithm (Fix & Hodges, 1951, Cover 1967) is employed with $k = 3$. It provides the three closest WS days to the target EC-day along with the corresponding weights, p_i, of day $i = 1,\ldots,3$ matching the EC target, decreasing with distance from the target. The Frankenstein day is formulated by combining the data of the three selected source WS-days, employing the weight p_i as a measure of how many continuous 10-min intervals to pick from each day. In our case the wind speed time series of the three closest source WS days are shown in Fig. 5a; they are split in the A, B and C continuous segments of 10-min intervals as per the p_i weights.



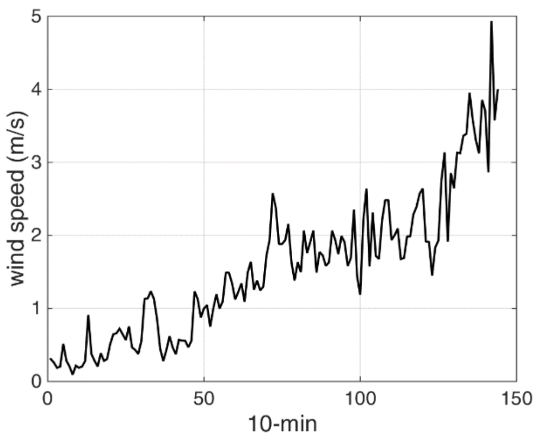
(a) three closest WS days



(b) A, B & C components of WS days combined to form Frankenstein day



(c) continuous-made Frankenstein day



(d) Frankenstein day scaled to match daily EC target

Figure 5. *Steps for generating the Frankenstein time-series from the closest weather station days.*

The Frankenstein day is generated by its A, B and C parts, each one randomly selected from a different source WS day, as shown in Fig. 5b. Still, the resulting time-series is discontinuous, thus the A and C components are scaled to close the gaps with B, i.e., by matching the average wind speed of the last 30-min of component A to the average wind speed of the first 30-mins of component B. The same process is also followed for component C by matching the average 30-min wind speed of C to this of the last 30-mins of component B (Fig. 5c). Given the typical lack of sufficient observations, the Frankenstein time-series does not match the target EC wind speed, thus it is uniformly scaled to allow matching the target. To achieve so, for each 10-min of the FS-day, the cell-level wind speed is determined via the LES data and the equivalent-to-the-Frankenstein-day EC-cell level time-series is scaled to match the daily EC target. The computed scale factor is finally assigned to the FS day and the resulting Frankenstein time-series is determined (Fig. 5d). The Frankenstein time-series is combined with the LES data of the selected prevailing wind direction to generate the spatially correlated Frankenstein WIMFs for all locations of interest that allow assessing risk both on an event basis and in the long-term.

Countless other improvements specific to each targeted weather parameter or different case at hand can also be incorporated but they will probably come out naturally as different applications are tackled. Still, even the baseline approach proposed herein can offer insight on how the Frankenstein days can be generated based on EC-data, historical WS measurements and pre-computed WIMFs.

CONCLUSIONS

The artificial wind time-histories that are generated comply with the daily values provided by Euro-CORDEX while at the same time they maintain the spatial variation of the WIMFs and the temporal correlation observed in the weather station measurements. They are not forecasts, i.e., they are not expected to be actually observed in the future but they are plausible realizations of what may happen, statistically speaking, in a future day. Although we do not necessarily believe every single 10-min of the time-histories, they conform with the long-term statistics provided by Euro-CORDEX and have the right temporal and spatial correlation to allow estimating risk on an event basis and in the long term. In many ways, they provide the needed information to connect coarse regional-level weather predictions with the resolution required for the asset-specific fragility and risk assessment of structures and infrastructures practiced by structural and geotechnical engineers.

ACKNOWLEDGMENTS

The first author gratefully acknowledges the financial support provided by the Eugenides Foundation in Greece (scholarship for doctoral studies in NTUA grant). Financial support has also been provided by the Innovation and Net-works Executive Agency (INEA) under the powers delegated by the European Commission through the Horizon 2020 program “PANOPTIS–Development of a decision support system for increasing the resilience of transportation infrastructure based on combined use of terrestrial and airborne sensors and advanced modelling tools”, Grant Agreement number 769129.

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