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Combining satellite and geospatial technologies for exploring rainstorm hazard over Mediterranean Central Area[1]

Nazzareno Diodato
MetEROBS – Met European Research Observatory, GEWEX-CEOP Network, World Climate Research Programme, via Monte Pino snc, 82100 Benevento Italy
e-mail: scodalabdiodato@gmail.com

1. Introduction

Modelling is not an alternative to observation but,
under certain circumstances, can be a powerful tool
in understanding observations and in developing and testing theory.

Mulligan M., and Wainwright J., 2004. Modelling and Model Building.
In: *Environmental Modelling*, Wiley, p. 2

Multiple Damaging Hydrological Events (MDHE, Petrucci & Polemio, 2003) are rapidly developing into deluges, flashfloods, floods, mudflows, accelerated erosion, and landslides (Kar & Hodgson, 2008; Younis et al., 2008), with tragic consequences on the viable habitat for humankind and ecosystems, and agriculture (Clarke & Rendell, 2005). In this context, MDHE could have more impact than the frequently cited hazard of global warming due to intensification of the hydrological cycle and the concentration of rainfall in sporadic- but more intense events (Allen & Ingram, 2002).
There is, in fact, evidence available from different parts of the world of a rising trend of natural disasters since 1993 (Sivakumar, 2005), included Medietarrean basin (Diodato & Bellocchi, 2010). For Southern Italy, in particular, the catstrophic events of Sarno in 1998 (Mazzarella & Diodato, 2002), with the more recent devastating deluges in Naples in 2001, 2003, 2004, 2006, and in southeastern of Sicily in 2009, were caused by extremes rain of 100-400 mm fallen in few hours over little areas. Therefore, global vision in remote sensing coverage and surveillance loop are important, since we do not know where an event might take place (Bacon et al., 2008). However, estimating rainfall from satellite imagery is rather complex (Ymeti, 2007), and due to limited success of deterministic rainstorm impact modelling techniques (Heneker et al., 2001).

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Also, while the literature on general model theory is vast, the aims of modellers usually consist of improving our understanding of a phenomenon and its process, and ultimately predicting the response of the landscape (Kelly et al., 2004; Diodato, 2005). In this context, data assimilation models, that combine ground measurements with remote sensing of rain-data, need to accommodate many specific aspects of the observations and models (Pan et al., 2008).

While surface data will always remain important cornerstones of reference for monitoring and modelling geospatial data, ground data suffers especially due to mutability of their patterns, even as the modeller is compelled to adapt frequently to maintain sufficient condition of temporal and spatial homogeneity, with time-series that are difficult to update.

The advent of Geographical Information Science (GISsci) can confer an innovative role on hazard modelling development, satellite data assimilation, model outputs uncertainty assessment, spatial data scaling, and mapping visualization. Although satellite data are regarded as indirect information and not as reliable as surface data, they can be of great help when used for scaling and assisting the modelling of a dynamic system (Su et al., 2008). However, the problem is that we have a significant increase in uncertainty when the measurements and forecasts move from the global to local scale, especially in their landscape response to change, such as downpours, heavy runoffs and flash-floods, deluges, sediment transport, and urban stormwater (after Beven, 2008). An interesting study for assessing rainfall impact was recently done by (Shoji & Kitaura, 2006) that analyzed precipitation with the parametric geostatistical approach in order to obtain information for predicting natural hazards caused by heavy rains.

In this paper, a different geostatistical criterion was applied – specifically a non-parametric approach – by transforming ground and satellite information into a continuous probabilistic response consistent with *soft* descriptions of hazards which is referred to in this study to mitigate the uncertainties in downscaling and geocomputational tracking (e.g., spatio-temporal non-homogeneity in the primary variable pattern, accuracy of the supplementary variables, errors involving sampling and hazard modelling). Processes operating to these multiple spatial and temporal scales, however, challenge the predictive capability of environmental models and integration or scaling of data from different sources (Allen et al., 2004). Non-parametric geostatistical multivariate analysis, via co-indicator coding criteria, is able to combine rainstorm indicators (which are recorded at sparse raingauge station-points) and supplementary satellite rain data (which are recorded across regular patterns). So that, the novelty of our approach lies in how methods and different tools might incorporate uncertainty associated with satellite data into a model of rainstorm hazard accounting, and to illustrate how model performs at sub-regional scale. In this way, the expansion of a Rainstorm Hazard Index (*RHI*) data from point to spatial information can be assessed with the Indicator CoKriging (ICK) technique, using Tropical Rainfall Mission Monitoring (TRMM–NASA) satellite rain data as covariate. Thus, spatial information is visualized with examples of probability estimations for different precipitation durations – ranging from 3 to 48 hours – and the quantification of hydrological hazard fields is done using probability maps of damaging rainstorms prone-areas.

2. Reference Data Sets and Methodology

2.1 Study area and problem setting

Heavy rainfall between 1951 and 2007 show Northern Mediterranean more affected than Southern one (Fig. 1a). Worldwide temporal pattern is also shown with a trend of hydrological disasters strongly increasing (Fig. 1b).
The rainstorms most perceived by the public are the large-scale damaging events; however, there is evidence that the most deadly floods are those with short lead times – flash floods – which in Mediterranean Europe have mostly a spatially limited character and can occur far away from major rivers (Lalsat et al., 2003).

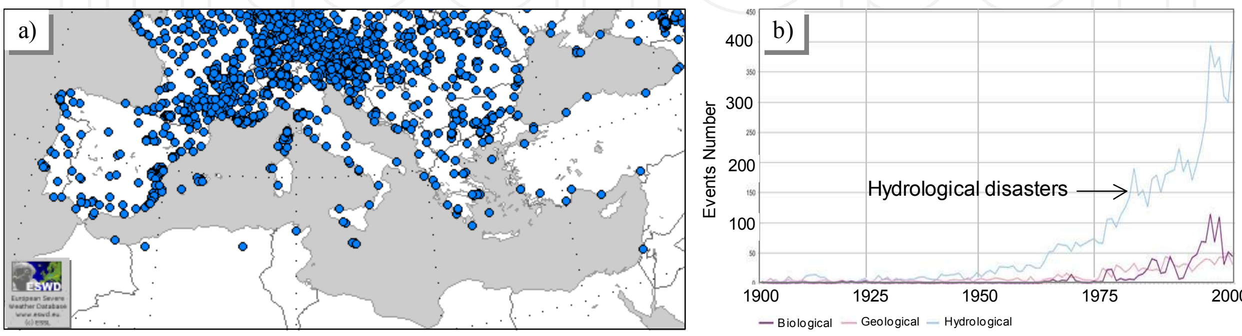

Fig. 1. (a): Occurrence of the heavy rain and hail during 1951–2007 period across Mediterranean lands (http://essl.org/cgi-bin/eswd/eswd.cgi); (**b**): Global natural disasters trends upon 1900-2005 period from EM-DAT (OFDA/CRED International Disaster Database, http://www.emdat.be).

In this respect, a test-area extending approximately 60000 km², was selected from Mediterranean central area (Fig. 2a corner). SCIA-APAT Database (www.apat.it/) was utilized for collecting rainfall ground data. However, ground data are not always updated and not all the networks uniformly coincide at all times with this database. Then satellite rain-data were also derived from the TRMM-NASA platform, algorithm 3B42 multi-satellite precipitation estimates (Huffman et al., 2007), that uses an optimal combination (HQ) of 2B-31, 2A-12, SSMI, AMSR, and AMSU precipitation estimates, with a resolution of 0.25x0.25 degree (about 25x25 km) grid boxes (http://disc.sci.gsfc.nasa.gov/).
In this way, a reference classification was constructed from RHI, driven by rainstorm events on 14 November 2004, 24 January 2003, and 4-5 May 1998. Data assimilation pattern in the region under study were obtained from 64 raingauges (Fig. 2a), and 143 supplementary satellite rain-grid-data (Fig. 2b).

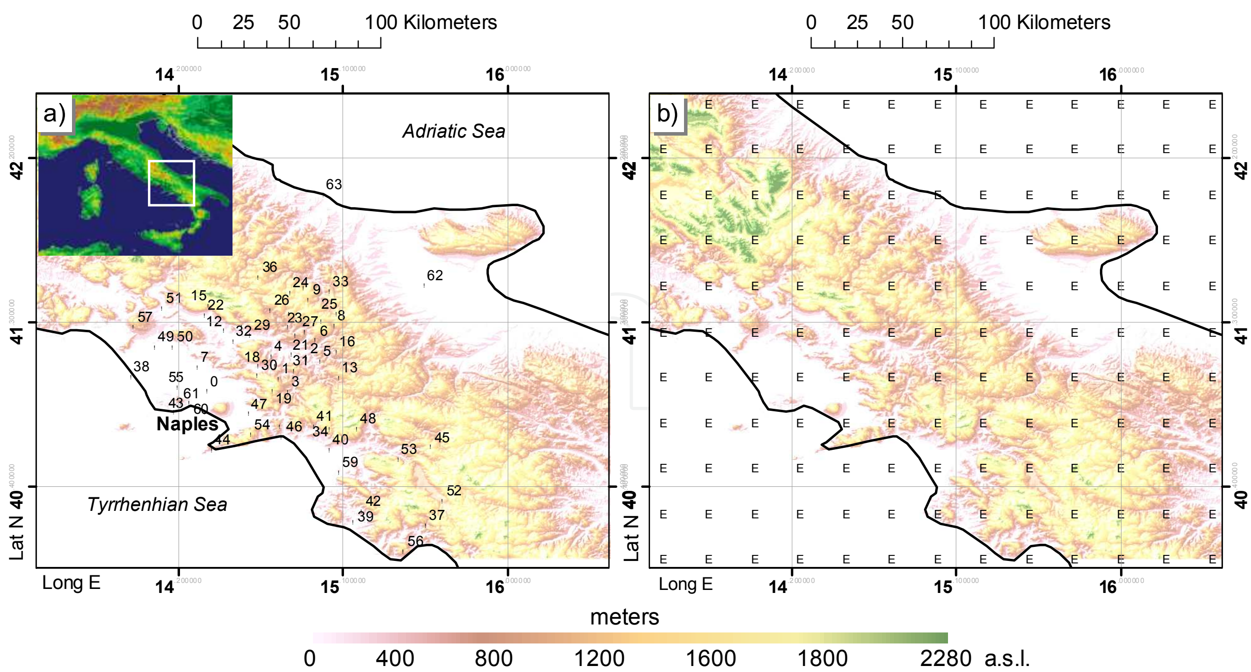

Fig. 2. (**a**): Geographical setting and data assimilation patterns from in-situ-raingauges with coded-station-points, and (**b**): TRMM-RS satellite rain data pixel centroid grid of 25 x 25 km, superimposed on elevation data of hillshade land derived from DEM (SRTM)-90 meters (http://srtm.csi.cgiar.org/).

2.2 Rainstorm hazard problem-solving logic process

Expert systems can be designed to model processes when carried out using the IF-THEN logic statement to impose an event contingent upon the condition (Moody & Katz, 2004).
Problem–solving logic process frameworks include first an invariant spatial model recognizing critical-thresholds from the response ratios between the two following components of the landscape:

- pulsing force that disturbs the system, including current rainstorm depth, and;
- resistance force, including storm variability that occurred in the system's climate history.

As a more concrete application, we can incorporate, for each rainy step of duration h at sampled location $\mathbf{s}_\alpha$, two processes into the rainstorm logic statement linking the the *RHI* to the following power equation (after Diodato, 2006; Diodato & Petrucci, 2009):

$$RHI_h\left(\mathrm{s}_\alpha\right) = \max:\left\{ \left[\frac{1+RSD_h}{f_{(Rclim)}} \right]^2_{h(\mathrm{s}_\alpha)} \right. \qquad \forall \quad h = 1 \ldots 48 \quad \text{hours} \tag{1}$$

where RSD_h is the Rain-Storm Depth (mm), that represents the **pulsing force** that disturbs the system during an event of duration h, and:

$$f_{(Rclim)} = \mathrm{Med}\left(RSD_h\right) - \left(8 - \sqrt{h}\right) \cdot S_{wet} \tag{2}$$

is a function that represents the **system resistance state**, that is the intrinsic ability of the system to resist change because of its history (recent and past). Med(RSD_h) –the threshold value – is the median of the annual maximum rainfall (mm) of duration h, and the term $(8–\sqrt{h})S_{wet}$, is a function adjusting the threshold value with the current variation of the soil humidity. As proxies of the soil humidity, three coefficients was introduced as S_{wet} equal to 0.5, 0, and 2 according to dry, humid, and very humid soil conditions before the event, respectively; these coefficients can be derived, in turn from remote sensing; the duration of rainstorm (h) under square root is to explain a major accommodation of the system for rainfall spanning over a longer period. Whereas, for each sampled location with a Rainstorm Hazard Index (*RHI*)$\rightarrow$0, no-rainstorm hazard occurs, and with *RHI* value barely over 1, the probability of occurrence of a rainstorm hazard commences at 0.50.

2.3 Matching coding approach for decision–making under uncertainty

While the above RHI–model is utilized to arrive at conclusions at the puntual-scale, the use of geostatistics method may help to overcome the inherent difficulties in spatial scaling, when the above *RHI* discrete data must accommodate a continuous spatial solution and data collection across sampled- and unsampled locations. Thus, the *RHI*–results are converted to a binary vector and matched to satellite rain-data under a GIS flow and supported by indicator cokriging technique (Fig. 3).
Consider the following information obtained over the study area:

- values of the random primary variable Z (*RHI*), at m locations $\mathbf{s}_\alpha$, $z(\mathbf{s}_\alpha)$, $\alpha = 1,2 \ldots n_1$; and
- $y(\mathbf{s})$ TRMM satellite rain-data at supplementary grid locations $\mathbf{s}$ within the area.

Indicator approach of the primary variable requires that all data be coded as local prior probability values. Precise measurements of z_k at hard data locations $\mathbf{s}_\alpha$ are then coded into a set of K binary (hard) indicator data defined as:

with
$$i\left(s_\alpha; z_k\right) = \begin{cases} 1 \rightarrow z\left(s_\alpha\right) > z_k \\ 0 \rightarrow \text{otherwise} \end{cases} \tag{3}$$

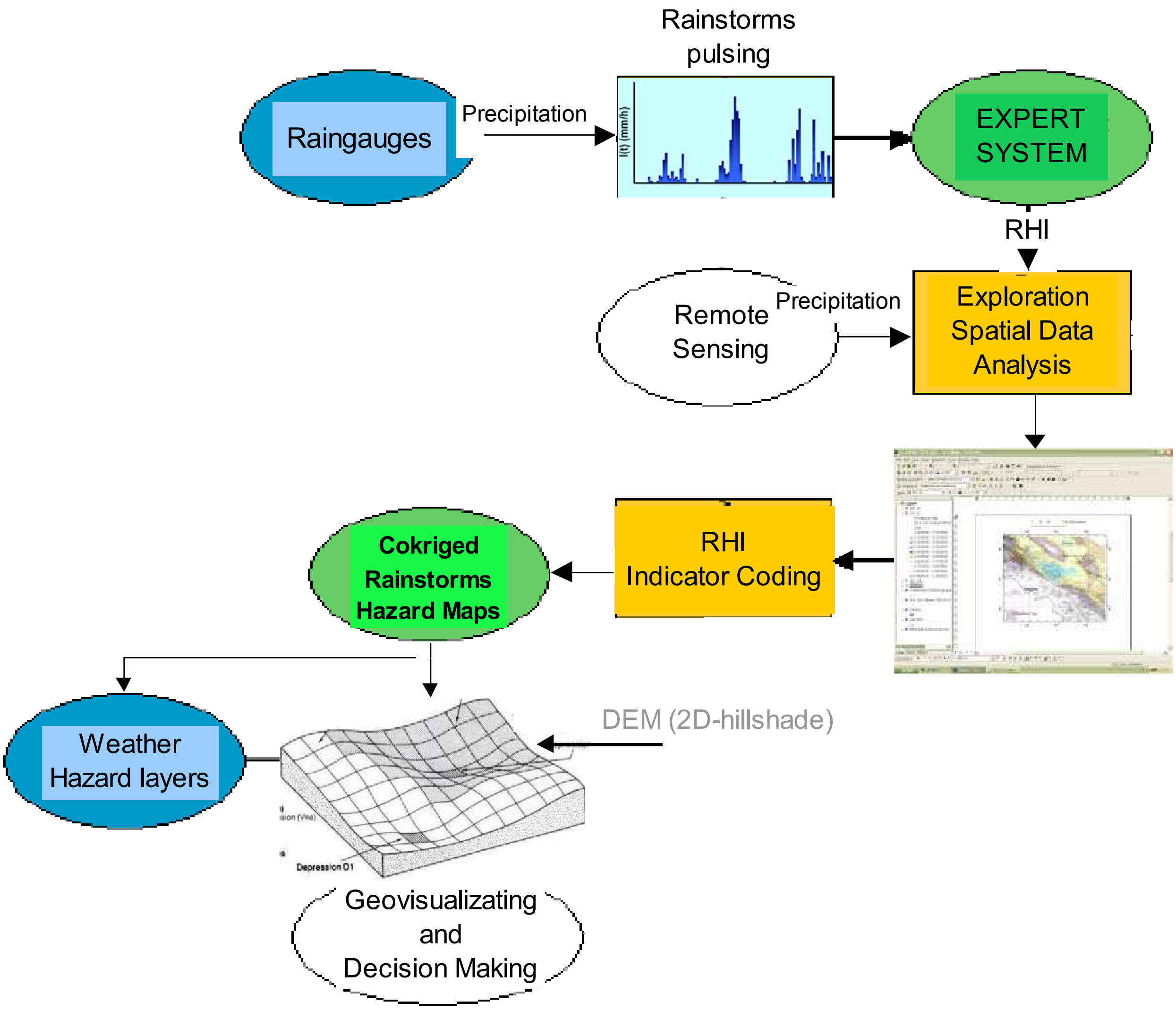

Fig. 3. Flow chart of process for estimation of rainstorm hazard mapping via GIS rules.

The z–values are *hard* in both senses: (1) they are directly derived from measurements of ground rainfall-data, and (2) are successively transformed into binary vector data. These measurements are often supplemented by a relatively large amount of indirect data, such as those conditioned on remotely sensed spectral response $y(\mathbf{s})$.
Each of these data provides only indirect information about the value of the variable Z. Using both *ground* and *satellite* information such as matching data, the approach is aimed at assessing the probability that the value of z at any unsampled site $\mathbf{s}$ is greater than a given critical z_k value. In this way, Indicator CoKriging (ICK) is able to take into account both the information to be processed together, and then used in the ordinary cokriging equations (Goovaerts, 1997; Johnston et al., 2001). To account for both categorial (*RHI*) and continuous (satellite data), we used standardized variables to produce composite indices compatible to indicator cokriging (Johnston et al., 2001; Hengle et al., 2004). So that, both covariance and cross-covariance functions were applied on the above standardized primary and auxiliary variables for incorporating exhaustively sampled satellite data using the indicator datum that is collocated with the location being estimated. Availability of coregionalization between indicator *ground* and *satellite* at critical values of *RHI* for each location $\mathbf{s}_o$ within the study area

allows a grid layer of: the hazard $\alpha(\mathbf{s}_\alpha)$ of declaring a location vulnerable to damage by rainstorms on the basis of the estimate $\left[I(\mathrm{s};z_k)\right]_{\mathrm{oIOK}}^{*}$ when actually $Z(\mathbf{s}) > z_k = p_c$ (critical value = 1).

3. Results and Discussions

3.1 Mapping the rainstorms hazard prone-areas

Figure 4 (a,b,c) shows high-probability cokriged (p>50%) maps of areas prone to rainstorm hazards (dark grey zones), and superimposed by areas where multiple damaging hydrological events (MDHE) were observed. It was found that areas with high probability of predicted hazard matched the area actually subject to injurious phenomena, such as severe erosion, landslides, floods, and mudflows.

The severity of the damage suffered in these areas was not uniform for each rainstorm level, i.e., the damage observed depended not only on the amount of rainfall but also on the sensitivity of each specific landscape and on soil humidity (others topographical conditions were not considered in this work).

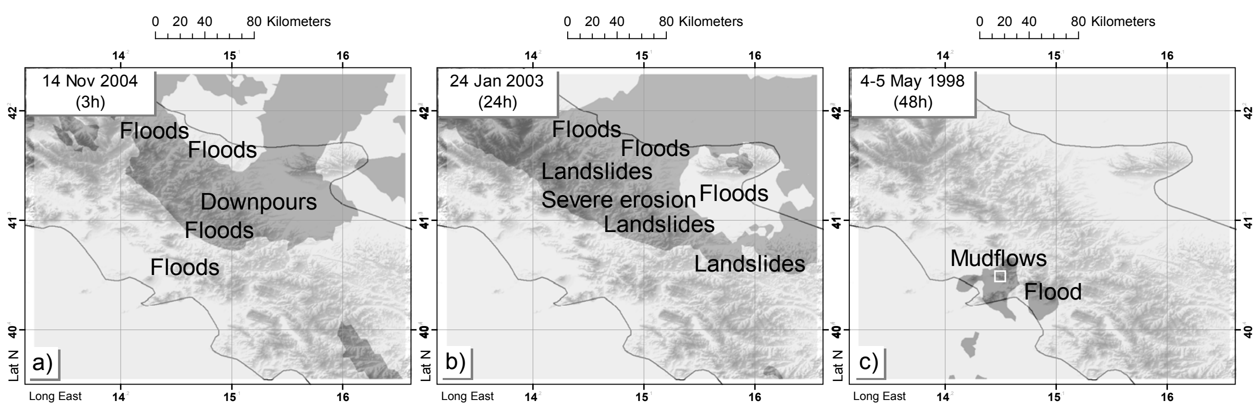

Fig. 4. High-probability (p>50%) cokriged maps of areas prone to rainstorm hazards (dark grey zone) for rainstorms of duration 3, 24, and 48 hours (a, b, and c, respectively). Note: the damaging hydrological events superimposed were almost all matched by the cokriged model.

The most extreme hydrogeomorphological processes occur over orographically complex terrain where vegetation is sparse (especially lands that are under autumn tilling, or after the rainy season), and where drainage systems may be obstructed by sediment erosion to contain large volumes of runoff. Prolonged rain usually occurs during the winter season only, when rainstorm prone-areas assume winding configurations, as for instance in Fig. 4b. On the contrary, MDHE are more spatially limited in the warm season (May-September), but more intensive, such as those which occurred on 14 November 2004 (Fig. 4a). Although the event of May 4-5, 1998 was expected to be of lower intensity, because of its long duration, the impact was catastrophic at the Sarno location (Campania region), where the several mudflows destroyed over one hundred people (Fig. 4c). This occurred because the meteorological perturbation originated from convective-clouds in larger systems, which are today more dominant in rain-producing mechanisms of high-impact over small areas (Dünkeloh & Jacobeit, 2003). This complexity is reflected in stormy pattern concentrate to the end of summer, as it is possible observe by positive anomalies of rain amount in

September occur during the recent decade (1999-2008), compared to the climatological period (1950-2000) (Fig. 5a).
The graph of Figure 5b also suggests that Southern Italy is subjected to a increasing precipitation, in term of intensity and of course of hazard, within September months spanning from 1948 to 2009. After 1996 in fact, rain rates were unusually very high, showing an abrupt change during the last decade. This can be an important advice when RHI modelling is used in an operative phase, where the climate information and human experiences becoming essential for successful completion an alert forecasts.

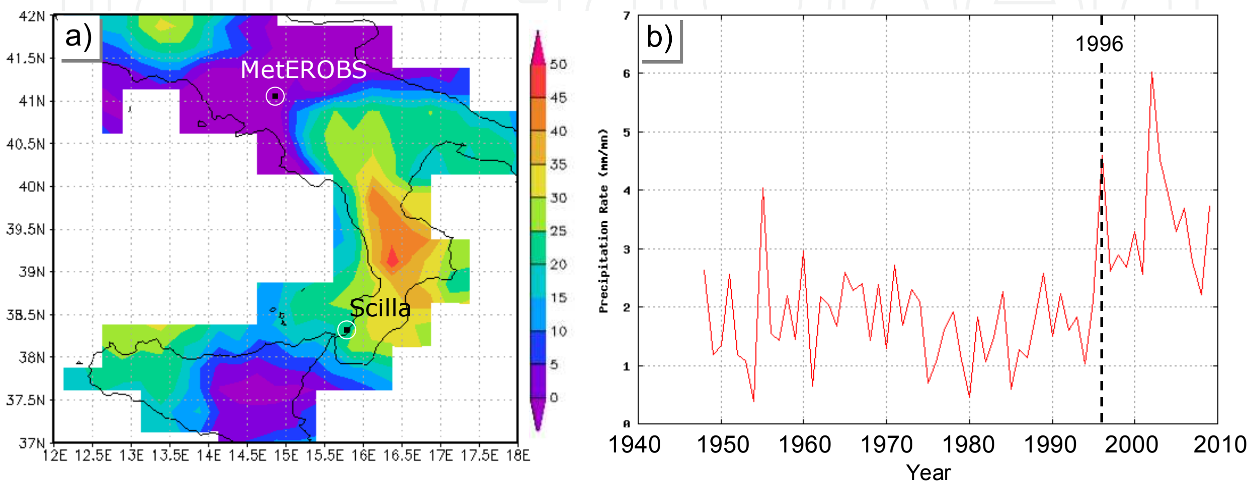

Fig. 5. (**a**): Spatial pattern of the September rain anomalies (mm) during recent decade (2000-2008) compared to climatological rain (1950-2000) upon Southern Italy (arranged from TRMM remote sensing by NASA Earth Science Data); (**b**): September rain rate evolution from 1948 to 2009 for the same region (from NOAA, ESRL Physical Sciences Division http://www.esrl.noaa.gov/ Acker & Leptoukh, 2007).

In this respect, the our results show that sub-regional rainstorm hazard modelling can provide probability maps for damaging events in Italy with a spatial variability resolution of approximately 20 km. Spatially finer estimates (e.g., at local-scale: < 10 km) can be ensured only with the availability of more accurate and detailed supplementary satellite-rain data, although, as noted by Anagnostou (2004), all satellite sensors are affected by errors originating from the non-unique, non-linear relationship of rainfall characteristics to observations and by sampling frequency and sensor resolution issues.

4. Conclusion

The model presented here provided the minimum but valuable set of data from which a rough tool for estimating early impacts soon after rainstorms can be derived. Damaging rainstorms collected for this retrospective experiment are documented in the category of localized events. Impact of the damage was determined by an optimum scaling critical value for predicting hazard prone-areas of three rainstorm types, although the *RHI*–model is capable of performing with data of storms of different intensities. These first results show that sub-regional rainstorm hazard modeling can provide probability maps for damaging events in Italy with a spatial variability resolution of approximately 20 km. Spatially finer estimates can be ensured only with the availability of more accurate- and detailed satellite-rain data, or during forecast stages, if real-time monitoring is implemented on an operational basis, where supplementary satellite information is then replaced by Quantitative Precipitation Forecasting.

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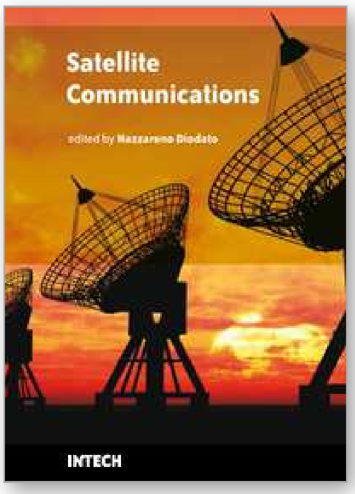

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This study is motivated by the need to give the reader a broad view of the developments, key concepts, and technologies related to information society evolution, with a focus on the wireless communications and geoinformation technologies and their role in the environment. Giving perspective, it aims at assisting people active in the industry, the public sector, and Earth science fields as well, by providing a base for their continued work and thinking.