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Investigating the Impact of Extreme Rainfall Events on Individual Perception of Climate Change

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Abstract— In this paper, we explore the concept of *climatic awareness*, which refers to the evolution over time of individual perception of climate change. To illustrate this concept, we propose an extension of a mathematical model of awareness based on Markov decision processes, taking into account high-frequency rainfall data recorded in Sicily. We focus on understanding how individuals develop their awareness over time and which are the factors influencing this process. This analysis allows us to introduce the *Climate Aware* individuals -capable of processing cross-cutting information- and the *Climate Susceptible* individuals-the majority of the population, more sensitive to external events. We therefore identify customized strategies for policymakers, which can operate mainly on *Climate Susceptible* individuals, encouraging them to take aware decisions toward sustainable development.

1. Introduction

Over the last few years, an increasing public concern on the phenomenon of climate change has risen. This has been induced by the presence of several climate extreme events. Among such phenomena, extreme rainfall events have proved to become more and more common and disruptive. For instance, in the Italian region of Sicily, almost 300 mm of rain were recorded in 2021. This amount corresponds to nearly half of the average annual rainfall, and the abrupt rainfalls caused damages and disruptions in the city surroundings [1].

In order to fight against climate change, a double action needs to be undertaken. If on the one hand policymakers should be made aware of the climatic situation changing, and should take relevant political and social actions, it is also true that on the other hand the awareness in the population should improve.

This is the reason why, together with the need of taking actions against climate change, there is the need of exploring ways of increasing climate awareness in the overall population. This, in fact, could induce the change in human behaviour, towards a more climatically sustainable and less disruptive way of living, in order to stop or reduce the spread of climate change [2, 3].

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As is well known from the scientific literature, all kinds of climate data, in particular rainfall time series, are generally non linear and unpredictable [4, 5]. This is also evidenced by the fact that nonlinear approaches have been increasingly used to analyze and study climate change, as can be seen in [4], where a novel clustering method based on complex networks is used. In this work, we intend to study the effects of *climatic* non-linearities in human behaviors and decisions, particularly in the individual awareness dynamics. With that purpose in mind, we exploit the dataset presented in our previous work [6], where we used a clustering algorithm to detect extreme rainfall events in Sicily, and we merge those findings with the awareness human model proposed in [7].

In particular, we model the behaviour of intuitive (I) and analytical (A) individuals, driven by "tacit knowledge" and quantitative data, respectively. We study the effects of extreme events in their behaviour, by extending our previous work [6]. We also focus on the model parameters, looking for transition values which could discriminate the two personalities.

The paper is structured as follows. In Section 2 we give a brief overview of the dataset structure. In Section 3 we describe the mathematical model. In Section 4 we present the experiments developed, and Section 5 is devoted to conclusions and future developments.

2. Materials

In this study we use the RSE dataset (the Rainfall Sicily Extreme dataset) introduced in [6], which is composed by geographical rainfall records with a 10 minutes periodicity from 2009 to 2021, and which was provided by SIAS, the Servizio Informativo Agrometeorologico Siciliano.

Without loss of generality, we reduce the dataset dimensionality by computing the moving average with step 10 of the time series, grouped by days. This is justified by the previous findings in [6], where the maximum per day (*md*) indicator emerged as one of those characterizing extreme stations. Figure 1, for instance, reports the data used for the station gauges of Catania (panel **(a)**) and Palermo (panel **(b)**), where unusually extreme events can be noticed in the case of Catania in 2021.

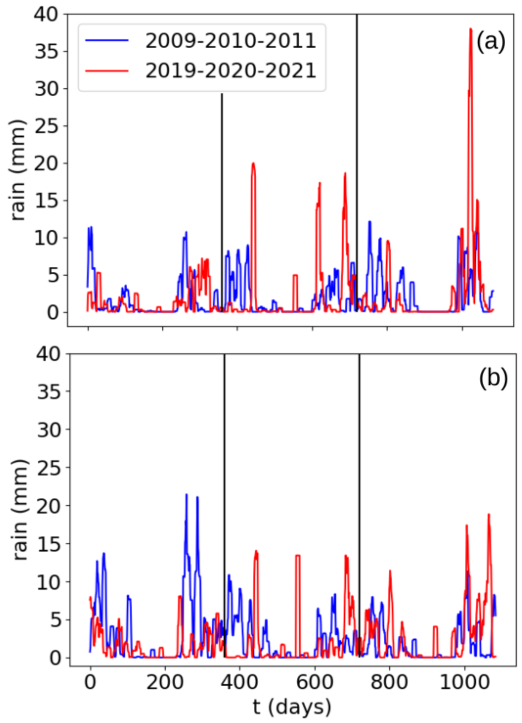

Figure 1: Moving average of step 10 of daily rainfall events. **(a)** Catania. **(b)** Palermo.

3. The Mathematical Model

This section describes the mathematical formalism, describing the model of aware behaviour grounded on Markov's Decision Processes (MDPs) used in this work to study the influence of climatic data in human decisions.

The underlying assumption is that the level of awareness of the individual has a relevant impact on their well-being from a global point of view: physical, psychological, and emotional, and has a considerable impact on their choices. By considering a Markovian decision process, the current state incorporates all the history of the Decision Maker (DM), so that their awareness is a state embodying, to some extent, all the past of the individual: from their personality, values, and beliefs developed over a lifetime, to their education and past experiences.

An MDP is a tuple $M = (S, U, P, r)$ where S is a finite set of states, U is a finite set of actions, $P : S \times S \times U \to [0, 1]$ is a transition probability function, and $r : S \times U \to R$ is a reward function.

At each time instant $t = 0, 1, 2, \ldots, T$, the individual is defined by their level of awareness $s_t \in S = [0, 1]$, and is required to make a decision $u_t \in U = [0, 1]$ in the present by taking into account the outcomes they will receive throughout the finite time horizon T. In particular, the action/choice ranges from a fully intuitive decision ($u_t = 0$) to a fully analytic decision ($u_t = 1$).

The reasoning propensity $p_r \in [0, 1]$ is a value characteristic of the single individual which represents their attitude in processing the information about the decision problem, taking values in a continuum between the two extreme attitudes called intuitive ($p_r = 0$) and analytical ($p_r = 1$), assuming in this way that both are always involved, with different amounts, in any decision, according to the dichotomy largely adopted in dual process theories and economics [8].

The state s_t of the DM evolves according to a not-deterministic dynamics, ruled by:

$$s_{t+1} = f(s_t, u_t, w_t) = s_t + w_t, \tag{1}$$

where the future level of awareness of the individual depends on the current state s_t, the choices u_t, and it is subjected to some uncertainty represented by a stochastic variable $w_t \in W$, according to a certain probability P, which presents three components specifying *Forward* $P^F(u_t)$, *Stationary* $P^S(u_t)$, and *Backward* $P^B(u_t)$ probabilities.

According to the assumption that awareness is related to the individual's well-being, the reward function incorporates a positive dependence on the current level of awareness s_t. On the other hand, the reward function must incorporate the costs of data acquisition and elaboration to find possible solutions to a given problem. Therefore, the more the decision implies analytical reasoning the more resources it needs in terms of time, personal energy, and monetary resources. Mathematically, the higher u_t the more analytical the reasoning of the DM, and so the more resources consumed:

$$r_t(s_t, u_t) = \alpha_b s_t - \alpha_c u_t, \tag{2}$$

where α_b and α_c weight the benefits of a given state s and the costs of a given decision u at time t.

The future discount δ of an expected reward is the weight the individual assigns to the present state with respect to the next one, i.e. when they have a not-null probability of transitioning to state s' from state s, performing a choice u. Specifically, $0 \le \delta \le \delta_{\max}$: when $\delta = 0$, the future is not considered, then the higher the value of δ, the higher the weight given by the agent to the future.

The objective value function the individual has to maximize in the set of available decisions u, reads as follows:

$$V_t = \left(r_t(s_t, u_t) + \sum_{\tau=t+1}^{T} \delta^{\tau} E\left[r_\tau(s'_\tau, u_\tau) \right] \right), \tag{3}$$

where the expected value E of the reward for future states s'_τ, takes into account an external stochastic source of uncertainty and the different importance the DM assigns to increasing, decreasing, or unchanging future states.

Moreover, the value $r_T(s_t)$ at final time T is fixed and depends exponentially on the state so as to drive the system dynamics towards higher states. Then, the maximization problem is solved through an algorithm of backward induction, starting from the last value and reconstructing step by step the sequence of the optimal decisions until the initial time.

In this study, the mathematical model is solved by considering each instant t as a single day. Moreover, we replace δ with a time dependent function $\delta(t)$, consisting of the corresponding rainfall measurement at time t, in order to analyze how extreme rainfall events influence decisions in the context of climate change. As explained in section 2, this value corresponds to the average of the data recorded in the previous 10 days, likely assuming that individuals process what they experienced with a certain delay.

4. Experiments and Results

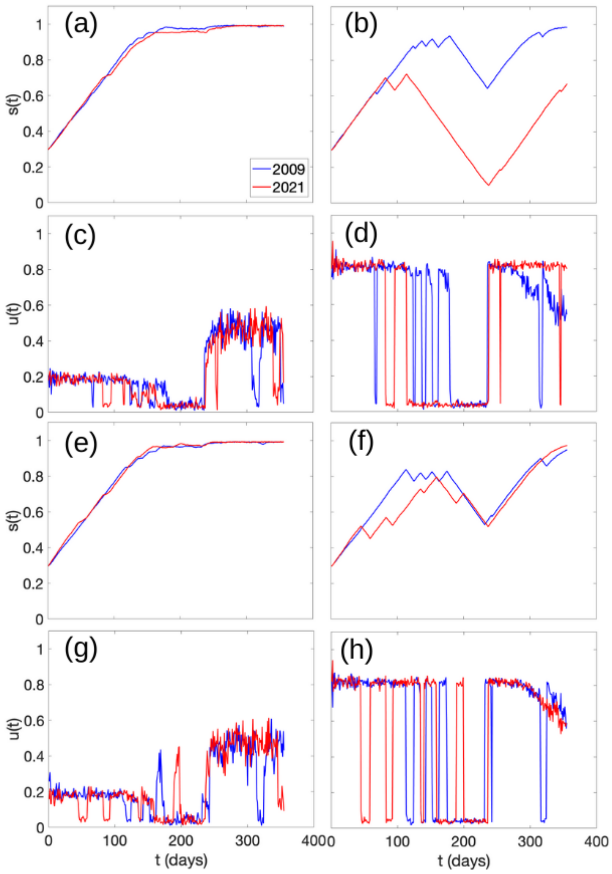

Figure 2: Temporal comparison: 2009 and 2021. **Catania-Palermo**. State dynamics of (I) **(a)-(e)** and (A) **(b)-(f)** individuals. Decision over time of (I) **(c)-(g)** and (A) **(d)-(h)** individuals.

According to the theoretical model described in section 3, we found a baseline configuration of the parameters to perform the numerical simulations. Moreover, several Sicilian sites have been considered, including Augusta, Catania, Palermo and Siracusa for the years 2009 and 2021. As reported in [6], the year 2021 showed extreme events in all cases except for Palermo, while the year 2009 did not present extreme events in any case. As explained in section 3, we performed the simulations replacing the constant parameter δ with the real rainfall measurements from the RSE dataset.

In Figure 2, we show the evolution over time of both the state s_t, i.e. the awareness, and decisions u_t of the two types of individuals investigated in this paper for Catania (panel **(a)** to panel **(d)**) and Palermo (panel **(e)** to panel **(h)**). Panels **(a)** and **(e)** refer to the intuitive individual (I), who, regardless of the experiences, manages to increase their awareness to the maximum value. Consistently with the model, in panels **(c)** and **(g)**, the decision is intuitive, thus allowing the (I) individual to increase the transition probability towards higher states (for both Catania and Palermo). Panels **(b)** and **(f)** refer to the analytical individual (A), who, on the contrary, results very susceptible to events involving them. In panel **(b)** regarding Catania, in fact, there is a significant difference between the blue line (2009) and the red line (2021). This occurs because, as seen in Figure 1 and reported in [6], the 2021 rainfall events in Catania were significantly more intense than in 2009. Similarly, in panel **(f)** a big difference between the two years is not present, as the rainfall events in Palermo are not so different from each other (Figure 1). In the cases of (A) individuals, decisions are optimal for high values of u_t, then when the associate decisions are low, the state may drop dramatically, such as in the central days of panels **(d)** and **(h)**).

The (A) individual, therefore, seems to be very sensitive to extreme rainfall events: the more intense the events, the more their state decreases, as if such individuals are excessively upset by the presence of extraordinary events.

We could therefore say that (I) individuals are more autonomous, unconditioned, and capable of assimilating and process information. On the other hand, the (A) individuals result very sensitive to their direct experiences and reactive to the data observed.

In conclusion, we are able to identify two characters that react differently to extreme rainfall events: the Climate Aware (CA) and the Climate Susceptible (CS) individuals.

As mentioned at the beginning of the section, we extended our analysis to other cities, in particular to Augusta and Siracusa. Moreover, we studied the sensitivity of the p_r parameter by performing additional extensive simulations. The goal of this further analysis is to find a critical threshold for p_r separating the two observed attitudes.

Figure 3 reports the behavior of individuals on all the considered localities. The parameter p_r varies in the interval [0.3,0.7] with a step of 0.05, where the minimum and the maximum values of the interval represent two prototypical (CA) and (CS) individuals, respectively. The figure rows correspond to different cities (Catania, Palermo, Augusta and Siracusa), while the columns refer to the years 2009 (no extreme events) and 2021 (extreme events), respectively, according to the findings in [6]. We notice that in 2009 the changing of p_r affects slightly the individual behavior, while stronger changes in the dynamics are observed in 2021 for the locations of Catania, Augusta and Siracusa, where extreme events occurred. The case of Palermo, where only moderate differences in the dynamics are observed also for 2021, confirms this result. In con-

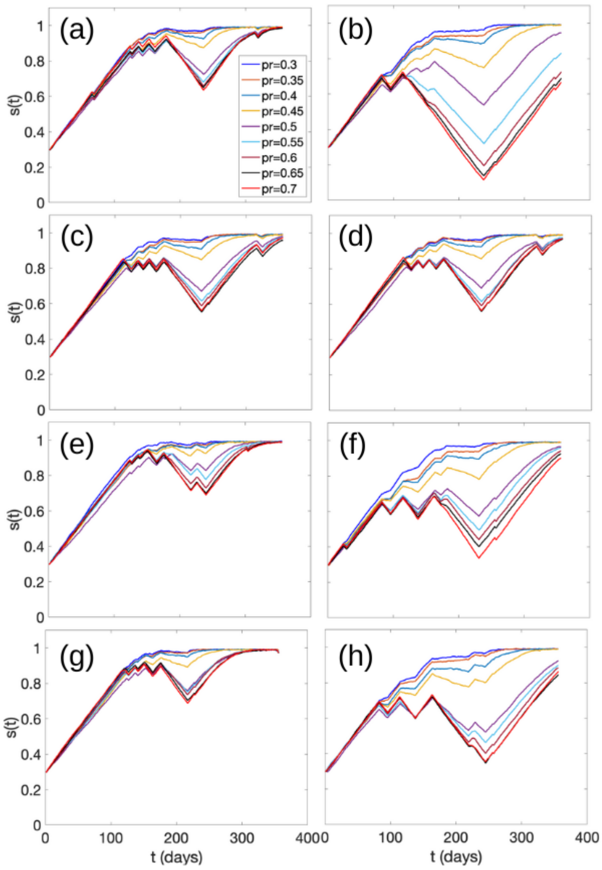

Figure 3: From $p_r = 0.3$ (CA) to $p_r = 0.7$ (CS) with step 0.05. **2009/2021**. Catania **(a)-(b)** Palermo **(c)-(d)** Augusta **(e)-(f)** Siracusa **(g)-(h)**.

clusion, the data sensitivity grows by increasing p_r more abruptly when considering extreme locations. This suggests the presence of a critical transition from (CA) to (CS) individuals, occurring approximately at $p_r = 0.45$.

5. Conclusions

The model presented in this paper validates and confirms the results obtained in [6]. Indeed, in all of the locations clustered as extreme in that paper, the critical transition from Climate Aware to Climate Susceptible individuals is more evident.

In addition, the results might suggest that effective actions the policymakers should take regard mainly (CS) individuals, trying to bring them below the critical transition by attempting to lower down the individual p_r parameter. This can be done by creating knowledge that is less tied to single data but broader and more interconnected. The determination of factors changing the inferential propensity parameter, can be supported by attitude surveys on the local population, considering both universal and specific factors.

According to [9], each country has its own relatively unique set of interrelationships. Therefore, national and regional programs aiming to increase citizen engagement with climate change must be adapted to the unique context of each country, especially in the developing world.

Moreover, the authors in [9] found that worldwide, educational attainment is the single strongest predictor of climate change awareness. In Latin America and Europe, risk perceptions are related to the anthropogenic nature of climate change, whereas in many African and Asian countries these are related to the local temperature change.

In conclusion, the literature suggests that the considered reasoning propensity parameter p_r will be certainly related to the individual's basic education, the climate literacy, and the understanding of the micro to macro interactions mechanisms influencing climate change. Therefore, acting on those factors will produce a change in the p_r parameter, thus allowing individuals to pass from (CS) to (CA) attitude, by fostering active engagement and experience of people on the dramatic effects of climate change rather than spreading alarms and fear, creating more general awareness and broadening the spectrum of knowledge.

Acknowledgments

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