

Modeling the synergistic relation between social learning and sustainable behaviors in the Italian city of Siena

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ABSTRACT

Promoting sustainable behaviors is a central component of climate-change mitigation and can be framed as a large-scale social dilemma, where individual incentives may conflict with collective benefits. How do urban interaction structures and social-learning mechanisms shape the persistence of environmentally sustainable behaviors among people who live in or regularly frequent a city? In this paper, we use agent-based modeling calibrated with real data and game theory to investigate how different network topologies and an environmental coupling mechanism affect synergistically sustainable behavior in a heterogeneous population composed of different types of players. We analyze four model configurations, combining an idealized regular setting and a georeferenced representation of Siena with geographical and small-world interaction networks. We find that stronger coupling to the local social environment is related to sustainable behavior in all cases. However, the Siena geographical configuration remains the least cooperative, suggesting that its urban structure and the strongly interconnected social structure, may limit the diffusion of cooperation and sustainable behavior. Finally, fixed-strategy agents appear elements reducing the system's ability to self-organize into cooperative configurations.

1. Introduction

Climate change represents one of the most pressing challenges of the twenty-first century, with far-reaching consequences for ecosystems, societies, and economies worldwide. Its impacts – including rising global temperatures, more frequent and intense extreme weather events, sea-level rise, biodiversity loss, and increasing risks to food and water security – are largely driven by human activities, particularly greenhouse gas emissions from fossil fuel combustion, land-use change, and industrial processes [1–5]. Mitigating these effects requires coordinated action at multiple levels, from international agreements and governmental policies to local initiatives and individual behavioral change.

While large-scale interventions and technological solutions are essential, a growing body of research highlights the pivotal role of individual and collective behaviors in the transition toward sustainability [6–9]. Everyday actions such as energy consumption choices, waste reduction, transportation habits, and resource management significantly contribute to greenhouse gas emissions and environmental degradation [10,11]. Encouraging citizens to adopt more sustainable lifestyles is therefore a crucial complement to top-down climate policies. Such collective shifts rely on cooperation among individuals, whose coordinated actions can drive systemic change toward sustainability.

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Cooperation is the act through which individuals choose to behave in ways that benefit others – often at personal cost – leading to outcomes that are collectively advantageous. Understanding how and why cooperation emerges has been a central topic across disciplines such as evolutionary biology, economics, sociology, and physics [12,13].

Social dilemmas offer a powerful theoretical framework for studying the emergence of cooperation, as they capture situations in which individually rational choices conflict with the collective optimum [14]. In these scenarios, cooperation yields the best group outcome, yet individuals face incentives to defect and free-ride on others' efforts. Climate change mitigation is a paradigmatic large-scale social dilemma: adopting pro-environmental behaviors (e.g., reducing emissions, changing consumption patterns) entails immediate private costs, whereas the benefits are diffuse and long-term [15]. From this perspective, promoting sustainable behavior is a collective action problem in which individuals must coordinate their decisions for the common good. Understanding the mechanisms that foster cooperation between individuals is therefore essential for developing policies and interventions that effectively drive pro-environmental change.

To investigate how cooperative behavior can emerge and evolve in such context, it is crucial to adopt modeling approaches that explicitly account for the interplay between individual decision-making and collective dynamics. Agent-based models (ABMs) provide a particularly powerful framework for this purpose, as they represent societies as complex systems composed of autonomous, heterogeneous agents who interact with one another and with their environment according to simple behavioral rules. Through these interactions, ABMs allow us to explore how micro-level decisions – driven by individual preferences, perceptions, and social influences – aggregate into macro-level patterns such as the diffusion of sustainable practices or the persistence of unsustainable behaviors [16–18].

Beyond their ability to capture interactions among heterogeneous individuals, agent-based models also require a framework for representing how agents make decisions. In many studies the decision-making process is formalized using game theory (GT) [19,20], which provides a mathematical description of strategic interactions among individuals whose choices are interdependent [21,22]. Game theory and evolutionary game theory (EGT) have long been a cornerstone for studying cooperation and social dilemmas, offering a rigorous framework to investigate how strategies evolve over time [13,23].

This approach is particularly relevant to our problem, as the promotion of sustainable behaviors can naturally be framed as a strategic interaction: individuals face choices that may involve environmentally responsible or less sustainable actions while considering the behavior of others and the associated costs and benefits [24,25]. At the modeling level, these choices are represented through the alternatives of cooperation and defection, which capture pro-environmental and non pro-environmental behavioral tendencies as they evolve under the influence of strategic incentives, social interactions, and imitation mechanisms. Their evolutionary dynamics can then be studied using classical games such as the Prisoner's Dilemma, Stag-Hunt, and Hawk-Dove. These canonical games capture distinct social mechanisms – ranging from self-interest with a temptation to defect, through herding, to anti-herding – that underlie real-world behavioral dynamics [26,27]. By embedding such game-theoretic dynamics into our ABM, we can explore how cooperation in sustainable behaviors emerges, spreads, and stabilizes within a population.

In [28] we developed a georeferenced ABM for the Italian city of Siena to investigate how cooperation in sustainable practices emerges and spreads among citizens. The model was calibrated using data collected through a survey conducted in 2023, in which 324 residents of Siena's historic center were asked about their opinions on climate change and their attitudes toward environmentally responsible behaviors.

In that model, agents represented individual citizens and made strategic decisions according to a GT framework, where cooperation denotes the adoption of more sustainable actions and defection denotes the adoption of less sustainable ones, taking into account strategic incentives and social interactions. Based on survey responses, agents were categorized into five behavioral types: (i) activists, who are fixed cooperators (A); (ii) deniers, who are fixed defectors (D); (iii) indifferent imitators of the best-performing neighbor, corresponding to Prisoner's Dilemma (PD) players; (iv) indifferent imitators of the local majority, corresponding to Stag-Hunt (SH) players; and (v) indifferent opponents of the local majority, corresponding to Hawk-Dove (HD) players. Agents interaction with their peers were modeled through two alternative network structures: a geographical proximity network, based on their spatial location within the city, and a small-world social network. Two model versions were implemented: the Basic Model (BM), in which agents are placed on a regular lattice, and the Siena Model (SM), georeferenced on the real urban network of the city. Numerical simulations revealed significant differences in cooperation levels across network structures, with the geographical Siena network consistently showing the lowest degree of cooperation.

In the present study, we extend this modeling framework in two key directions. First, we enrich the empirical foundation of the model by incorporating data from a new large-scale survey conducted in 2024, which collected 972 responses. Unlike the previous data collection, which focused exclusively on residents of Siena's historic center, the new survey includes not only local inhabitants but also non-residents who regularly spend time in the city for work, study, or tourism. Including these groups is crucial, as their daily behaviors – even if temporary – significantly contribute to the city's environmental footprint and influence the dynamics of sustainable practices [29,30]. The survey collects individual opinions on climate change and the propensity toward sustainable practices in various areas, such as waste sorting, cleaning public spaces, water and energy consumption, and the adoption of sustainable technologies. The resulting dataset is first analyzed statistically and then used to calibrate the agent-based model.

Second, following a growing body of research that recognizes the crucial role of external factors – such as the social and environmental context – in shaping individual decision-making [31–34], we introduce an environmental coupling mechanism that explicitly incorporates the influence of social learning into agents' strategic choices. In this extended formulation, each agent's decision is no longer based solely on its individual payoff but also on the state of its surrounding social environment. This is implemented through a fitness function defined as a weighted combination of the agent's personal payoff and the average performance of the most successful strategy in its neighborhood.

This extension allows us to explore how social learning from peers shapes the evolution of cooperation in sustainable behaviors. Specifically, we investigate how increasing the weight of environmental coupling influences the system's ability to sustain cooperation across different network topologies – namely, geographical and small-world structures – in both the Basic Model and the Siena Model. Moreover, we examine how social learning dynamics can counteract the temptation to defect, even when incentives for unsustainable behavior are strong.

The paper is organized as follows: Section 2 presents the empirical dataset and the modeling framework adopted in this study, including the network structures, the classification of behavioral types, the game-theoretic interpretation, and the environmental-coupling mechanism. Section 3 reports the main results, first discussing the survey findings and the socio-demographic patterns in climate-change awareness, and then presenting the outcomes of the numerical simulations for the different model configurations. Finally, Section 4 summarizes the main findings, discusses their implications, and outlines possible directions for future research. The full survey used for data collection in this study is reported in [Appendix A](#).

2. Materials and methods

In this section, we describe the empirical data and the modeling framework adopted in this study. In detail, Section 2.1 presents the dataset collected through a large-scale survey conducted in 2024, specifically designed for this research to capture citizens' opinions, awareness, and sustainable behaviors related to climate change. These data are not only analyzed from a statistical perspective but also used to calibrate the ABM, which represents individuals as autonomous decision-makers interacting within different network structures. Section 2.2 provides a detailed description of the mathematical formulation of the ABM, including the behavioral rules and the introduction of the social learning mechanism.

2.1. Data and preliminary results

The dataset used in this study was obtained through a survey conducted between June and December 2024 as an extension of the previous 2023 data collection described in [28]. The survey was distributed with the support of the Municipality of Siena, which promoted the initiative through its official communication channels and social media pages jointly with the collaboration of Prometeo Srl, a company developing artificial intelligence and data analysis tools for private and public institutions. A total of 972 responses were collected, corresponding to the agents of the ABM model.

The main objective of this new survey was to gather information on citizens' opinions, perceptions, and behaviors in relation to climate change and environmental sustainability. Unlike the 2023 survey, which targeted only residents of Siena's historic center, the new data collection also included non-resident groups, such as students, workers, and tourists who regularly spend time in the city. This inclusion is crucial, as Siena's collective environmental impact is determined not only by its permanent inhabitants, but also by the daily practices of temporary or transient populations, whose behaviors significantly influence energy consumption, waste production, and the city's environmental footprint.

The survey consisted of twenty-six questions organized into three sections, as reported in [Table A.1](#) in [Appendix A](#). The first section of the survey (S.1) includes ten questions of different nature, aimed at assessing both respondents' awareness of climate change and their pro-environmental behaviors. Specifically, question Q1 consists of six sub-items (Q1.1–Q1.6) designed to evaluate the level of awareness and perception of citizens regarding climate change and its main consequences — such as its anthropogenic origin, its impact on ecosystems, and its influence on human health and lifestyle. Questions Q2–Q9 investigate participants' sustainable behaviors and pro-environmental engagement in everyday life, covering multiple domains of individual and collective responsibility. Specifically, they explore actions related to energy and water consumption, participation in waste sorting, reuse of materials, proper disposal of hazardous waste, attention to the environmental impact of personal purchases, participation in public cleaning activities, interest in adopting low-impact technologies, and behavioral conformity or deviation from local social norms regarding waste sorting. The last question of S.1 – question Q10 – investigates respondents' perception of their neighbors' waste-sorting behavior, distinguishing between different categories of materials: paper, plastic, organic waste, hazardous waste and bulky waste.

The second section of the survey (S.2) includes five questions (Q11–Q15) designed to assess respondents' knowledge of climate change and its effects, with a focus on their understanding of key environmental concepts such as the definition of climate change, mitigation and adaptation strategies, and recent global climate trends.

The third section of the survey (S.3) collects socio-demographic information to characterize the respondents and contextualize their behavioral and knowledge patterns. It includes questions on residency status (resident, non-resident worker or student, tourist or visitor), age, gender, educational level, employment status and household income class (Q16–Q20 and Q26).

The sample includes a total of 972 respondents. A majority are residents of Siena, both in and outside the historic center (62.0%), followed by non-resident workers (13.1%), non-resident students (5.1%), occasional visitors (4.6%), and tourists (1.4%). About 13.7% of participants preferred not to answer. In terms of gender, female respondents represent 53.6%, male respondents 31.3%, while 0.2% identified as non-binary, and 14.9% preferred not to answer. Regarding age, the sample is characterized by the following percentages across age groups: 4.6% (14–23 years), 14.5% (24–33), 10.1% (34–43), 19.2% (44–53), 24.5% (54–63), 9.5% (64–73), and 2.4% (74+), while 15.2% preferred not to answer. Educational level is relatively high: 29.7% of respondents hold a high school diploma, 13.0% a bachelor's degree, 23.5% a master's degree, 8.4% a post-graduate specialization, and 6.4% a PhD. Lower educational levels are less represented (0.1% no qualification, 0.3% primary school, 3.2% middle school). About 15.4% preferred not to answer. Employment status shows that 58.1% of participants are employed, 10.2% retired, 9.1% students, 2.1% unemployed,

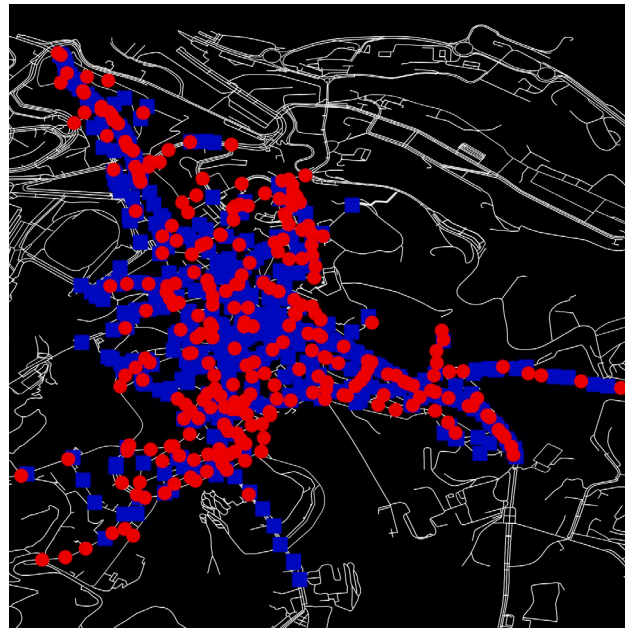


Fig. 1. *Spatial distribution of survey respondents.* Geographical distribution of the 972 respondents on the map of Siena, distinguishing between residents of the historic center (red dots) and non-residents of the historic center (blue squares).

and 3.8% other categories, while 16.8% preferred not to answer. Finally, regarding household income, 36.0% report a medium monthly income, 17.0% report a low one, and 12.2% a high one. A total of 34.8% preferred not to answer.

Questions Q21–Q25 were designed to georeference respondents' answers on the map of Siena. Specifically, residents living within the historic center were asked to indicate their street of residence, allowing their position to be mapped accordingly. Non-residents of the historic center, on the other hand, were asked to report the street within the city center that they most frequently visit for reasons such as work, study, leisure, or religious activities, and were consequently placed at that location. Fig. 1 shows the spatial distribution of the 972 respondents mapped onto the street network of Siena, where red dots represent residents of the historic center whereas blue squares represent non-residents. The map confirms that both groups spatially cover the entire historic center of Siena, which exhibits the characteristic Y-shaped urban morphology. The above information enables the construction of an explicit representation of social interactions based on spatial proximity, forming the empirical basis for the georeferenced version of the agent-based model described in Section 2.2.

Beyond their descriptive interest, responses to questions are also used to classify respondents into five behavioral profiles that will serve as agent types in the ABM: activists, deniers, indifferent imitators of the best neighbor, indifferent imitators and opponents of the local majority [28]. This classification focuses on individual awareness and self-reported pro-environmental behaviors, and it is therefore based exclusively on items Q1–Q9. In particular, Q10 is excluded because it concerns respondents' perceptions of their neighbors' behavior rather than their own; Q11–Q15 are excluded because they assess factual climate-related knowledge, which does not necessarily coincide with actual behavioral patterns [35,36]; and Q16–Q26 are socio-demographic and geographical questions, used to characterize the sample but not to define agents' behavioral types. The classification procedure and its connection to the game-theoretic agent types are described in detail in Section 2.2. All other information provided by the survey are used to develop and tune the mathematical model described in the following section.

2.2. Mathematical model

We model the population of Siena by means of an agent-based model, in which each individual is represented as an autonomous agent that repeatedly interacts with its neighbors and updates its behavior over time. The system consists of $N = 972$ agents, corresponding one-to-one to the respondents of the 2024 survey. At each time step every agent chooses between two alternative strategies: cooperation (C) and defection (D). In our framework, these strategies are associated with the adoption or non-adoption of a pro-environmental orientation. However, cooperation and defection should not be understood as direct one-to-one counterparts of the self-reported sustainable behaviors collected through the survey. Survey-based behavioral items measure declared behaviors at the time of data collection and are used, together with awareness items, to characterize agents at initialization, whereas cooperation and defection are dynamic outcomes that emerge over time from agents' interactions and social learning mechanisms. The decision-making process follows a game-theoretic formulation, where agents interact strategically with their neighbors on a given network, and their payoffs depend both on their own strategy and on the strategies adopted by their neighbors. The resulting payoffs, combined with a social-learning mechanism, drive the evolution of strategies over time.

2.2.1. Network structure

The model is developed in two versions, which differ in the spatial embedding of agents and in the way local interactions are defined, following the same general structure adopted in our previous work [28]. The first version, referred to as the Basic Model, represents an idealized city with a perfectly regular topological structure. The second version, referred to as the Siena Model, is instead grounded in the empirical geography of Siena's historic center, reproducing more realistic spatial patterns of interaction based on the survey data.

In the Basic Model, agents are placed on a regular 36×27 square lattice, so that each of the 972 nodes represents one individual. The geographical network is defined by a Moore neighborhood without periodic boundary conditions: each internal node is connected to its eight nearest neighbors, while nodes on the boundary and in the corners have fewer neighbors. In this sense, the Basic Model can be interpreted as an idealized city with a perfectly regular spatial and topological structure, where – up to boundary effects – all agents share the same local interaction pattern.

In the Siena Model, agents are instead positioned on the empirical map of Siena's historic center. Residents are located on their reported street of residence, whereas non-residents are located on the street they reported as most frequently visited in the city center, as shown in Fig. 1. The geographical network is then built by connecting any pair of agents whose geographical distance is smaller than a fixed radius of about 100 m. This value corresponds to the smallest radius for which the empirical spatial network remains connected, and it yields an average degree $\langle k \rangle \approx 35$, consistent with the Siena Model network in [28]. In this way, the local interaction structure reflects the actual spatial distribution of the study area while ensuring that all agents belong to the same connected interaction network.

For both spatial embeddings we consider two alternative graph topologies, capturing different dimensions of social interaction: the geographical and the small-world network. The geographical network is the one defined above (regular lattice for the Basic Model, distance-based network for the Siena Model) and captures local interactions between neighbors, thus reflecting proximity-based influence. In this setting, two agents are connected only if they are neighbors in physical space, so information and behavioral influence can propagate through short-range contacts along the underlying spatial structure of the city. To account for social ties that are not constrained by spatial proximity, for example friendships or work relationships, we also derive a small-world network from the geographical one. Empirical studies of social networks have shown that such systems typically exhibit high clustering and short average path lengths, a combination that is well captured by small-world topologies [37–39]. Starting from the geographical structure, each edge is rewired with a certain probability, denoted as the small-world rewiring probability ($SWrp$) in the model, and replaced with a link to a randomly chosen node, following a procedure inspired by the Watts–Strogatz model [37]. This construction preserves a high clustering coefficient while strongly reducing the average path length, thus mimicking the “shortcuts” typical of realistic social networks.

2.2.2. Behavioral types and game-theoretic interpretation

The artificial population of $N = 972$ agents is partitioned into five behavioral types, corresponding to qualitatively different patterns of engagement with climate change and sustainability: activists, deniers, and a group of indifferent agents, the latter further divided into three subtypes - indifferent imitators of the best neighbor, indifferent imitators of the local majority, and indifferent opponents of the local majority. Behavioral types are inferred using items Q1–Q9 of the survey, which jointly capture climate-change awareness (Q1.1–Q1.6) and self-reported pro-environmental behaviors (Q2–Q9). Each respondent is classified into exactly one of the five profiles according to their pattern of answers, following the procedure introduced in our previous study [28] and adapted to the extended survey. As a first step, we quantify individual awareness of climate change and its consequences. For each agent i , we define $a_i \in [0, 1]$ as the average of the answers to questions Q1.1–Q1.6. This quantity provides a summary measure of how strongly the agent recognizes the anthropogenic origin and impacts of climate change across multiple dimensions, such as environmental, social, and health-related aspects. In addition, we compute the number of positive responses P_i and the negative ones N_i to questions Q2–Q8. For Q2–Q6, positive responses are options a or b and negative ones are options d or e ; for Q7–Q8, positive response is option a and negative one is option c (see Table A.1 in the Appendix for details on each option). Agents are then classified according to the rule reported in Algorithm 1.

Algorithm 1 Agent's Classification

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1: for each agent  $i$  do
2:   if ( $a_i \geq 0.7$ ) and [(Q6 and Q7 positive) or ( $P_i \geq 6$ )] then
3:      $Type(i) \leftarrow \text{ACTIVIST}$ 
4:   else if ( $a_i \leq 0.4$ ) and [(Q3 negative) or ( $N_i \geq 2$ )] then
5:      $Type(i) \leftarrow \text{DENIER}$ 
6:   else
7:      $Type(i) \leftarrow \text{INDIFFERENT}$ 
8:     Use Q9 to choose among the three indifferent subtypes:
9:     imitator of local majority / imitator of best neighbor / opponent of local majority
10:  end if
11: end for

```

More precisely, questions Q1.1–Q1.6 and Q2–Q8 are used to classify respondents into three macro-types: activists (A), deniers (D), and indifferent (I) agents. Qualitatively, questions Q6 and Q7 are treated as particularly informative for identifying activists,

Table 1

Comparison of the distribution of behavioral types in the 2023 survey (N = 324, historic-center residents only) and the 2024 survey (N = 972, residents and non-residents). Columns show the percentage of respondents classified as activists (A), deniers (D), and indifferent PD, SH, and HD players. The two distributions are highly consistent across years (Pearson's $R = 0.97$, p -value = 0.0047).

Agent type	2023	2024
<i>A</i>	10.19%	17.90%
<i>D</i>	4.63%	1.86%
<i>PD</i>	60.80%	70.47%
<i>SH</i>	13.89%	5.45%
<i>HD</i>	10.49%	4.32%

since paying attention to the environmental impact of purchases or participating in the cleaning of public spaces are deliberate and proactive choices, less driven by formal rules than other behaviors such as waste sorting or water and energy saving. Moreover, requiring at least six positive answers out of Q2–Q8 ensures that activists display a pervasive engagement across multiple domains of sustainable practices, and in particular that they almost surely answer positively to at least one between Q6 and Q7. A similar reasoning underlies the identification of deniers. Question Q3, which concerns participation in separate waste collection, is considered central because recycling has long been recognized as a strong and consolidated social norm. Moreover, giving negative answers to at least two of the seven items Q2–Q8 indicates a non-marginal resistance to sustainable habits across several relevant behaviors, and is therefore associated with deniers. Awareness and behavior-related items are intentionally combined in the classification procedure to ensure that the assigned profiles reflect consistency between respondents' environmental awareness and their declared behaviors. In other words, high environmental awareness alone is not sufficient to assign a respondent to the activist group unless it is accompanied by coherent self-reported sustainable behaviors. Similarly, low awareness alone is not considered sufficient to identify a denier unless it is also associated with negative behavioral indicators.

Question Q9 is used to characterize the behavioral orientation of indifferent agents with respect to social influence. This item focuses on waste sorting because it is a frequent, socially visible, and locally regulated pro-environmental practice in urban contexts. For this reason, it provides a suitable setting in which respondents can compare their own behavior with that of their neighbors. The three response options are interpreted as capturing three attitudes toward social norms: imitation of the local majority, opposition to the local majority, and imitation of the best-performing behavior. These orientations correspond, respectively, to conformist, anti-conformist, and self-interested agents.

From a game-theoretic perspective, the five behavioral profiles obtained from the survey are mapped onto distinct player types following our previous work [28] and the qualitative nature of the underlying games. Activists and deniers are modeled as players with unconditional strategies cooperate and defect, respectively. Indifferent agents, by contrast, update their behavior in response to social information. In particular, indifferent imitators of the best neighbor are treated as Prisoner's Dilemma (PD) players: in line with the classical interpretation of the PD as a paradigm of self-interested behavior undermining collective cooperation, they adopt at each step the locally best-performing strategy. Indifferent imitators of the local majority behave as Stag-Hunt (SH) coordination players, aligning with the most common strategy in their neighborhood. Finally, indifferent opponents of the local majority implement an anti-coordination rule analogous to the Hawk-Dove (HD) game, tending to choose the strategy opposite to the local majority.

Applying the classification rule reported in Algorithm 1 to the 2024 survey data yields the following macro-type composition of the population: 174 activists (A), 18 deniers (D), and 780 indifferent agents (I). Within the indifferent group, the classification yields 685 indifferent imitators of the best neighbor (PD players), 53 indifferent imitators of the local majority (SH players), and 42 indifferent opponents of the local majority (HD players).

As a check of the robustness of the classification procedure, we performed a 5-fold cross-validation analysis using the awareness items Q1.1–Q1.6 and the self-reported behavior items Q2–Q8 as predictors and the macro-type assigned by Algorithm 1 (activist, denier, or indifferent) as the response variable. Several standard supervised classifiers, including decision trees, k-nearest neighbors, support vector machines, and ensemble classifiers, were tested, and they consistently achieved high validation accuracies, around 97%. This indicates that the macro-types assigned by the algorithm are highly reproducible from the survey items and correspond to stable and learnable response patterns in the data.

The obtained distribution of behavioral types is used in both the Basic and the Siena Model, so that the only difference between the two model versions lies in their spatial embedding and network structure. This composition is very close to the one obtained in our previous 2023 survey of 324 residents of Siena's historic center [28]. The percentages of the five behavioral types in the two samples are reported in Table 1, showing a high consistency across years.

2.2.3. Interaction dynamics and strategy updating

In the model, each agent behaves as a player in a repeated game. At each time step t each agent chooses between the two strategies cooperation (C) and defection (D). Agents interact only with their neighbors on the chosen network: geographical or small-world in both the Basic and Siena model. For each agent i we denote by $\mathcal{N}_i$ the set of neighbors and by t_c the number of cooperating agents in $\mathcal{N}_i$.

Table 2

Color code for strategy changes of players. C = cooperation, D = defection.

Color	Previous round	Current round
Blue	C	C
Red	D	D
Green	C	D
Yellow	D	C

Following our previous work [28] and standard formulations in evolutionary game theory [40–42], the individual payoff s_i of agent i is defined as

$$s_i = \begin{cases} t_c & \text{if agent } i \text{ cooperates,} \\ \alpha \times t_c & \text{otherwise,} \end{cases} \quad (1)$$

where $\alpha \in [0, 5]$ is the defection award parameter, representing the benefit each player gets from defection.

This formulation assumes that the benefit from cooperation increases proportionally with the number of cooperating neighbors. Cooperators therefore gain more when sustainable behaviors are widespread in their local environment. Defectors, instead, obtain a benefit that is a multiple α of the number of cooperating neighbors, meaning that they profit from others' sustainable actions without contributing themselves.

Taking inspiration by a large body of research [31–34], which shows that individual decisions are not based only on personal payoffs, but are also shaped by the surrounding social environment and by the perceived success of others' behavior, we introduce a new fitness function F_i for each agent i that combines its own payoff with information on the locally most successful strategy. Let $\bar{s}_C$ and $\bar{s}_D$ be the average scores of cooperating and defecting neighbors of agent i , respectively. We then define

$$F_i = (1 - \mu)s_i + \mu \max(\bar{s}_C, \bar{s}_D) \quad (2)$$

where $\mu \in [0, 1]$ is the environmental coupling parameter. Thus F_i is a weighted combination of the agent's own score and the average performance of the currently most successful strategy in its neighborhood, enabling the learning mechanism. When $\mu = 0$, similarly to [28], the fitness coincides with the individual payoff and agents ignore their social environment. As μ increases, agents increase the weight assigned to the best local strategy, thus learning from the most successful behavior observed in their context.

Once all agents have updated their score s_i and fitness F_i , they simultaneously choose their strategy according to their behavioral type:

- (A) players always cooperate.
- (D) players always defect.
- (PD) players select the same strategy as the agent with maximum fitness among their neighbors.
- (SH) players select the same strategy as the majority of their neighbors.
- (HD) players select the opposite strategy with respect to the majority of their neighbors.

For each agent, the evolution of strategies over time is visualized through a color code, as reported in Table 2. Specifically, (i) blue agents cooperate in both the current and previous rounds; (ii) red agents defect in both rounds; (iii) green agents defects in the current round and cooperated in the previous one; and (iv) yellow agents cooperate in the current round and defected in the previous one. This representation allows us to track stable behaviors (blue/red) and recent switches in strategy (green/yellow) in the spatial patterns produced by the simulations.

2.2.4. Simulation parameters

The model depends on a set of parameters that control population size and composition, network structure, and strategic dynamics. In all simulations the population size and the distribution of behavioral types are fixed to the values inferred from the 2024 survey: $N = 972$ agents, with $N_A = 174$ activists, $N_D = 18$ deniers, $N_{PD} = 685$ indifferent imitators of the best neighbor (PD players), $N_{SH} = 53$ indifferent imitators of the local majority (SH players), and $N_{HD} = 42$ indifferent opponents of the local majority (HD players). The same composition is used in both the Basic and the Siena Model. Network topology is controlled by the small-world rewiring probability $SWrp$, which takes the value $SWrp = 0$ for the geographical networks and $SWrp = 0.05$ for the corresponding small-world networks. The initial fraction of cooperators, denoted by ic , is fixed to $ic = 0.5$: activists start as cooperators, deniers as defectors, and indifferent agents are assigned strategy C with probability ic and D otherwise. Consequently, at time $t = 0$ all agents are in a stable state (blue for cooperators and red for defectors), whereas the transition colors (green and yellow) can emerge only after subsequent strategy updates. The two key dynamical parameters are the defection award $\alpha \in [0, 5]$, which regulates the advantage of defectors in the score function (1), and the environmental coupling $\mu \in [0, 1]$, which controls the weight of the social environment in the fitness definition. In the numerical experiments reported in Section 3, we vary α and μ over their admissible ranges for both network structures (geographical and small-world) and both spatial embeddings (Basic and Siena Model), while keeping $SWrp$ and ic fixed as specified above (see Table 3).

Table 3
Model parameters.

Symbol	Description	Value/Range
N	Number of agents	972
N_A	Number of activists (A)	174
N_D	Number of deniers (D)	18
N_{PD}	Number of PD players	685
N_{SH}	Number of SH players	53
N_{HD}	Number of HD players	42
$SWrp$	Small-world rewiring probability	{0, 0.05}
ic	Initial fraction of cooperators	0.5
α	Defection award	[0, 5]
μ	Environmental coupling	[0, 1]

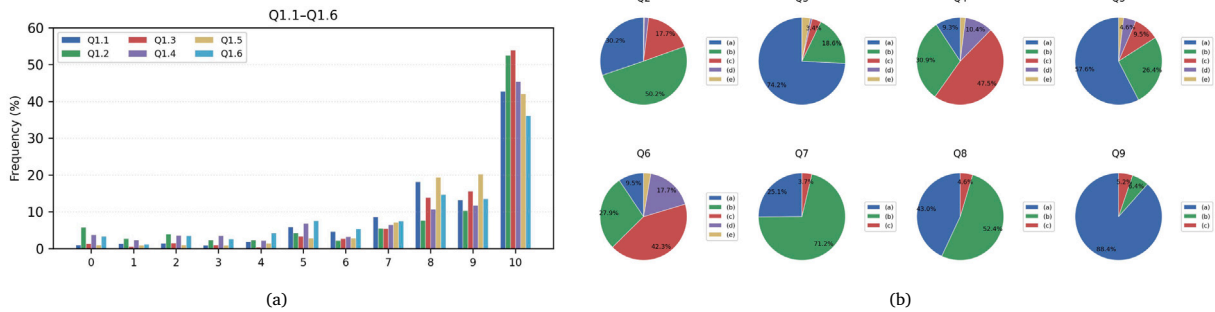


Fig. 2. Survey response distributions. Frequency distribution of responses to questions (a) Q1.1–Q1.6 on climate change awareness, (b) Q2–Q9 on self-reported pro-environmental behaviors. Answer options are coded as *a-e* or *a-c*, as appropriate, according to the wording reported in Table A.1 in Appendix A.

All simulations reported in the following section are run for $T = 100$ time steps and averaged over 50 independent realizations. Specifically, the randomization in the Basic and Siena geographic network consists of assigning at each run different player characteristics, while the randomization in the Basic and Siena small-world network is obtained by changing at each run the graph connection.

3. Results

In this section we present the main findings of the study. First, we present the 2024 survey findings, showing both overall response distributions and statistically significant differences in awareness across socio-demographic groups. Second, we present the outcomes of the agent-based model simulations, focusing on how cooperation levels depend on network topology and on the interplay between the defection award and the environmental coupling parameters.

3.1. Survey results and socio-demographic patterns in climate-change awareness

Survey responses provide a detailed picture of how respondents perceive climate change and to what extent they adopt pro-environmental practices in everyday life. Responses to the six awareness items Q1.1–Q1.6, measured on an 11-point numeric scale conceptually equivalent to a Likert-type scale [43,44], are strongly skewed toward the upper end of the scale, as shown in Fig. 2(a), indicating widespread recognition of climate change, its anthropogenic origin, and its impacts on ecosystems and human well-being. Questions Q2–Q9 address respondents' self-reported pro-environmental behaviors in everyday life. As shown in Fig. 2(b), responses indicate an overall positive behavioral profile, with the most consolidated practices related to energy and water saving (Q2), waste sorting (Q3), and proper disposal of hazardous waste (Q5), where about 80%, 92.8% and 84% of responses fall in the positive categories (*a* and *b*), respectively. Lower engagement emerges for material reuse (Q4), attention to the environmental impact of purchases (Q6), participation in public cleaning activities (Q7), and interest in low-impact technologies (Q8), where the percentage of positive responses (*a* and *b* for Q4 and Q6; *a* for Q7 and Q8) decreases to 40.2%, 37.4%, 25.1% and 43%, respectively. However the share of indifferent responses (*c* for Q4 and Q6; *b* for Q7 and Q8) remains higher than that of clearly negative ones, suggesting that respondents tend to exhibit a generally favorable or at least non-oppositional attitude toward pro-environmental behaviors, even when active engagement is limited.

Responses to Q10, which probes perceived neighbors' waste-sorting compliance across material categories, suggest a broadly positive assessment for the most common material categories (paper, multi-material, and organic waste). In contrast, perceived compliance decreases for categories that are less frequent and more demanding to manage (hazardous and bulky waste) which

respondents more often associate with incorrect disposal practices. Answers to the climate-knowledge items in Section S.2 (Q11–Q15) indicate a generally solid understanding of core concepts. Most respondents correctly identify the qualitative definitions of climate change and of mitigation and adaptation, whereas performance is weaker on the quantitative questions (Q14–Q15), which require recalling numerical estimates of temperature and sea-level rise. Descriptive figures relating to Q10–Q15 are reported in the supplementary material.

Having outlined the overall distributions of awareness, behaviors, and knowledge items, we next examine whether individual awareness is reflected in self-reported everyday practices. To this end, we relate the individual climate-change awareness score a_i introduced in Section 2.2.2 to a composite indicator of sustainable behavior. We compute the behavioral index b_i using items Q2–Q8 and omit Q9, since it captures behavioral alignment with neighbors rather than self-reported engagement in sustainable actions. Since Q2–Q8 use response scales of different lengths, we first recode each item onto an ordinal scale where larger values correspond to more sustainable responses, and we then normalize each recoded item to the $[0, 1]$ interval before aggregation, so that all items contribute comparably [45]. The individual behavior indicator is finally computed as the mean of the normalized scores across Q2–Q8. The Spearman rank correlation between awareness and the behavioral indicator is positive and statistically significant ($\rho = 0.29$, p -value < 0.001), suggesting that awareness and everyday practices are related but only moderately aligned, consistent with the well-documented knowledge-action gap in pro-environmental behavior [35,36]. This moderate association further supports the choice of considering both dimensions in the classification procedure described in Section 2.2.2, in order to ensure consistency between respondents' environmental attitudes and their declared practices.

Beyond these overall response distributions, we further examine whether climate-change awareness differs systematically across socio-demographic groups. To this end, we summarized responses to Q1.1–Q1.6 through heatmaps, as shown in Fig. 3, reporting group-level mean responses and standard deviations for each item. We then assessed group differences using non-parametric statistical tests: Kruskal–Wallis with Dunn post-hoc comparisons [46,47] for multi-group variables, and Wilcoxon–Mann–Whitney test [48,49] for binary variables. Fig. 3(a) shows that tourists (T) are systematically less aware than the other groups across most items; group differences are statistically significant for Q1.1, Q1.3, and Q1.5. A clear gender gap emerges in Fig. 3(b): women (F) report higher awareness than men (M) across all items, with statistically significant differences for Q1.1, Q1.3, Q1.4, Q1.5, Q1.6, in line with the eco-gender gap phenomenon analyzed in many studies [50–52]. Educational level displays a marked gradient, as shown in Fig. 3(c), with the middle-school group (MS) displaying the lowest values; heterogeneity is statistically significant for Q1.2, Q1.4, and Q1.6, mainly driven by contrasts between “Middle School” and higher education levels. Finally, respondents living outside the historic center (NC) tend to report higher awareness than those living within it (C), as shown in Fig. 3(d), with statistically significant differences for Q1.1 and Q1.5. The same analysis was also performed for age, employment status, and household income (heatmaps and full statistical outputs are reported in the Supplementary Material). Age-related differences point to lower awareness in older respondents for some items, but statistically significant heterogeneity emerges clearly only for Q1.4, where the 74+ group differs from the younger groups (24–33 and 34–43). For employment status, a significant difference is detected only for Q1.4, with retirees reporting lower awareness than workers and students. Finally, no statistically significant differences are found across income classes for any of the six awareness items.

3.2. Model results

In what follows, we analyze the outcomes of the agent-based model, focusing on the role of the environmental coupling parameter μ . When $\mu = 0$, agents' fitness coincides with their game payoff, so the model reduces to the framework introduced in our previous work [28], with the only difference that the calibration relies on the updated 2024 survey data. We consider the two model variants introduced in Section 2.2.1, namely the Basic Model and the Siena Model, each implemented on a geographical network and on a small-world network. Hereafter, we denote the resulting four configurations as BM-Geog, BM-SW, SM-Geog, and SM-SW, respectively. For each configuration, we ran simulations while varying the defection award parameter α . For each value of α , we computed the number of cooperators and defectors, corresponding to the number of blue (stable cooperators) and red (stable defectors) agents at the final time step $T = 100$, respectively. Both quantities were averaged over 50 independent realizations. This procedure gives two curves as functions of α : the cooperator and the defector curve. We define the critical threshold α_1 as the value of α at which these two curves intersect. Thus, for $\alpha < \alpha_1$, cooperation dominates, whereas for $\alpha > \alpha_1$, defection becomes prevalent. Fig. 4 shows two examples for the BM-Geog configuration illustrating the temporal evolution of the system, where we plot the number of cooperators and defectors (blue and red lines, respectively), together with the number of yellow and green agents, over time. Panel (a) corresponds to a case in which cooperation dominates, while panel (b) shows a regime in which defection prevails. Since α represents an incentive to defect, increasing α progressively undermines cooperation, as expected. The resulting α_1 values for each model configuration, reported in Table 4, are consistent with those obtained in our previous study [28].

In both the Basic and Siena model, α_1 is slightly higher under the small-world topology than under the corresponding geographical network, suggesting that when $\mu = 0$ long-range shortcuts may slightly facilitate the spread and persistence of cooperative behavior. Moreover, for a fixed topology, α_1 is systematically lower in the Siena Model than in the Basic Model, indicating that Siena urban structure makes cooperation more fragile and limits the diffusion of sustainable behavior.

We next explore the full parameter space by varying the environmental coupling parameter $\mu \in [0, 1]$ and computing the critical threshold α_1 for each value of μ and for each model configuration. Fig. 5 reports the resulting values $\alpha_1(\mu)$; more precisely, for each value of μ we plot the corresponding critical threshold α_1 for all the model configurations. When $\alpha_1 = 5$, no intersection between the cooperator and defector curves is observed within the explored interval $[0, 5]$. In these cases, the cooperator curve remains above the defector curve throughout the whole explored range, meaning that cooperation remains dominant for all tested values of α .

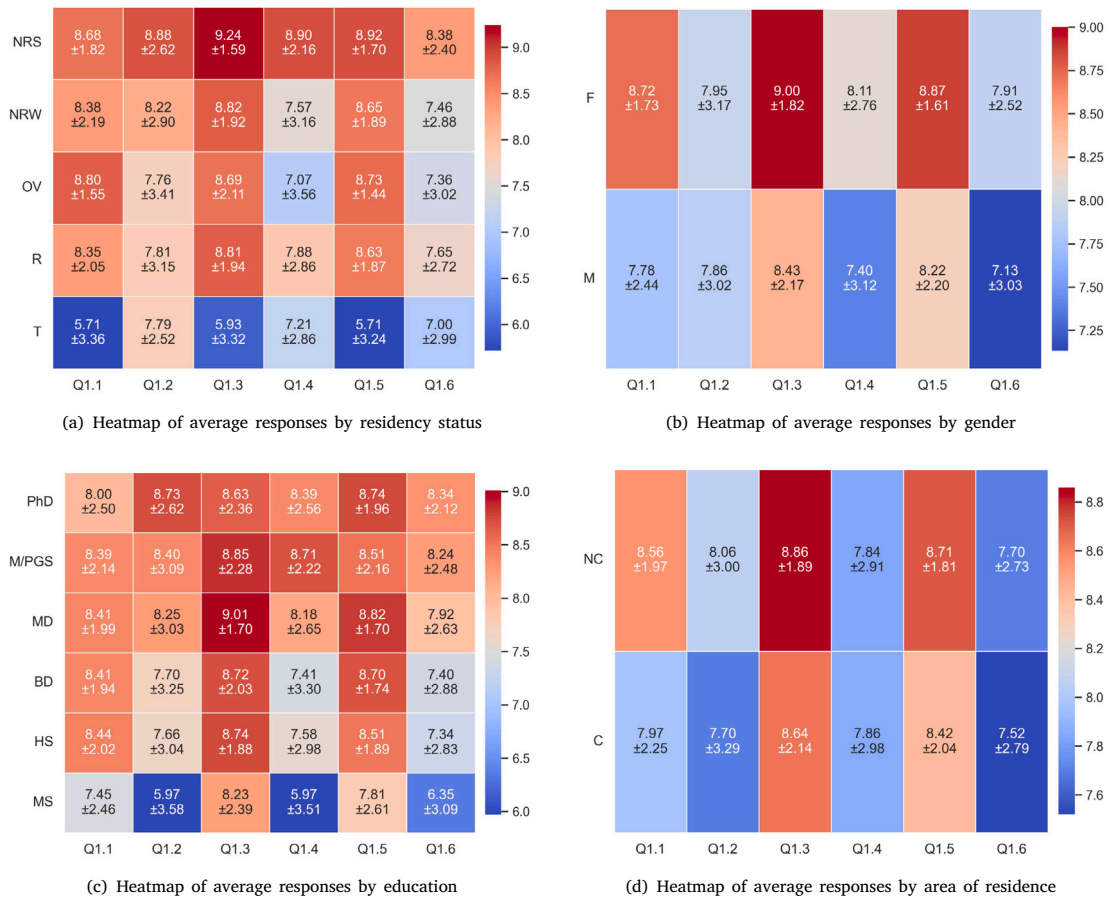


Fig. 3. Climate-change awareness across socio-demographic groups. Heatmaps of climate-change awareness by socio-demographic groups. Columns report the six awareness items Q1.1–Q1.6, while rows correspond to the categories of the grouping variable. Each cell reports the group mean response μ and standard deviation σ for the corresponding question ($\mu \pm \sigma$). Panels refer to: (a) residency status (R = resident; NRS = non-resident student; NRW = non-resident worker; OV = occasional visitor; T = tourist); (b) gender (F = female; M = male); (c) educational level (PhD; M/PGS = Master/Post-graduate specialization; MD = Master's degree; BD = Bachelor's degree; HS = High School Diploma; MS = Middle School Diploma); and (d) area of residence (C = historic center; NC = outside the historic center).

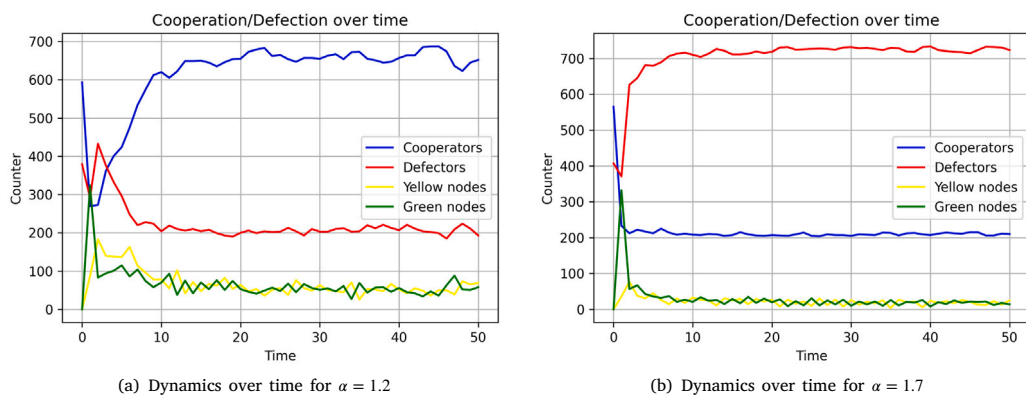


Fig. 4. Temporal dynamics of cooperation and defection. Evolution over time of cooperators and defectors (blue and red lines, respectively), together with the yellow and green agents, for two values of the defection award parameter α , with $\mu = 0$.

Table 4

Critical thresholds α_1 at $\mu = 0$ for the Basic (BM) and Siena models (SM) on geographical (Geog) and small-world (SW) networks.

Basic model (BM)	Siena model (SM)
(Geog) $\alpha_1 = 1.31$	(Geog) $\alpha_1 = 1.05$
(SW) $\alpha_1 = 1.36$	(SW) $\alpha_1 = 1.08$

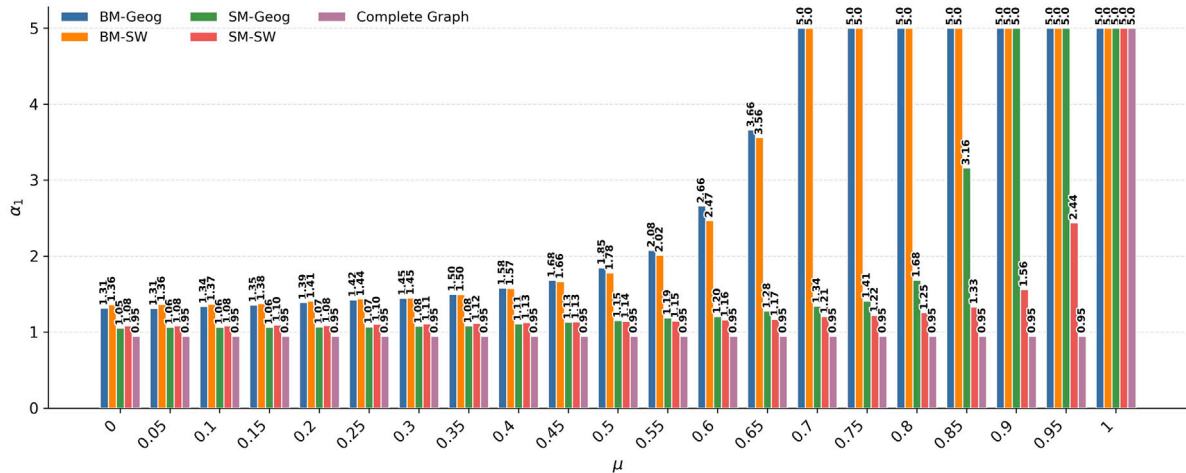


Fig. 5. Cooperation-defection critical threshold as a function of environmental coupling. Critical thresholds α_1 as a function of the environmental coupling μ across the four model configurations (BM-Geog, BM-SW, SM-Geog, SM-SW) and a complete network scenario.

To verify that the simulation time horizon is sufficient to capture the long-run behavior of the system, we performed a convergence diagnostic based on the standard deviations of the fractions of cooperators, defectors, yellow and green agents over the last 30 time steps, averaged over 50 independent realizations for each pair (μ, α) . The corresponding heatmaps for the four model configurations are reported in the Supplementary Material (Fig. S10, S11, S12, S13). This analysis shows that, in most regions of the (μ, α) parameter space, these standard deviations are zero or very close to zero. Therefore, the system reaches either a fully stationary state, when the standard deviations are zero and the final fractions become constant, or a statistically stationary regime, when small bounded fluctuations persist around stable average values. Larger residual fluctuations are localized in restricted regions of the parameter space, mainly near the cooperation-defection transition. In all configurations, however, their magnitude remains limited, supporting the use of $T = 100$ as a sufficient time horizon to characterize the long-run behavior of the system.

Across the four configurations BM-Geog, BM-SW, SM-Geog, SM-SW, we observe that α_1 increases monotonically with μ . Since α quantifies the incentive to defect, this implies that stronger coupling to the local social environment systematically enhances the resilience of cooperation, allowing cooperative outcomes to persist even when defection becomes more rewarding. This shift can be understood by examining how the fitness landscape changes with μ , as shown in Fig. 6. Specifically, we plot the average fitness of cooperators (panel (a)) and defectors (panel (b)) at the final time step as a function of α , for different values of μ . For each μ , the corresponding critical threshold α_1 is marked by a black dot. For a fixed value of α , increasing μ generally raises the average fitness of both cooperators and defectors; however, this increase becomes more pronounced for cooperators when $\alpha \gtrsim 1$, which is the region where defection would be expected to become increasingly advantageous. Fig. 6 illustrates this effect for BM-Geog (similar qualitative patterns are obtained for the other three model configurations). The resulting widening of the cooperators' fitness advantage makes cooperative neighbors more likely to be imitated by PD agents, who account for the largest share of the population, so cooperative configurations become harder to destabilize and the cooperation-defection transition shifts toward larger α .

The rate at which α_1 increases with μ varies markedly across configurations. In both the Basic Model configurations, the effect of environmental coupling is already substantial at intermediate values of μ : around $\mu = 0.55$ the system sustains high cooperation even for strong incentives to defect, with α_1 rising to values around 2. Full cooperation is reached for $\mu \geq 0.7$, where α_1 saturates at the upper bound of the explored range. In contrast, the Siena model configurations are consistently the most fragile, exhibiting systematically lower α_1 at the same μ , and requiring much stronger coupling to the social environment to achieve comparable outcomes: full cooperation emerges only for $\mu \geq 0.9$ in the SM-Geog and for $\mu = 1$ in the SM-SW. This highlights that, in the empirically grounded Siena setting, social learning must be substantially stronger for cooperative behavior to persist under comparable defection incentives, confirming the higher fragility of the Siena Model. Moreover, the effect of the small-world topology is not uniform across the range of μ . For low values of the environmental coupling, the small-world network yields α_1 values that are either slightly higher than, or very close to, those of the corresponding geographical network, suggesting a weak positive effect of long-range shortcuts on cooperation. For larger μ , however, this pattern tends to reverse: α_1 becomes lower under the small-world

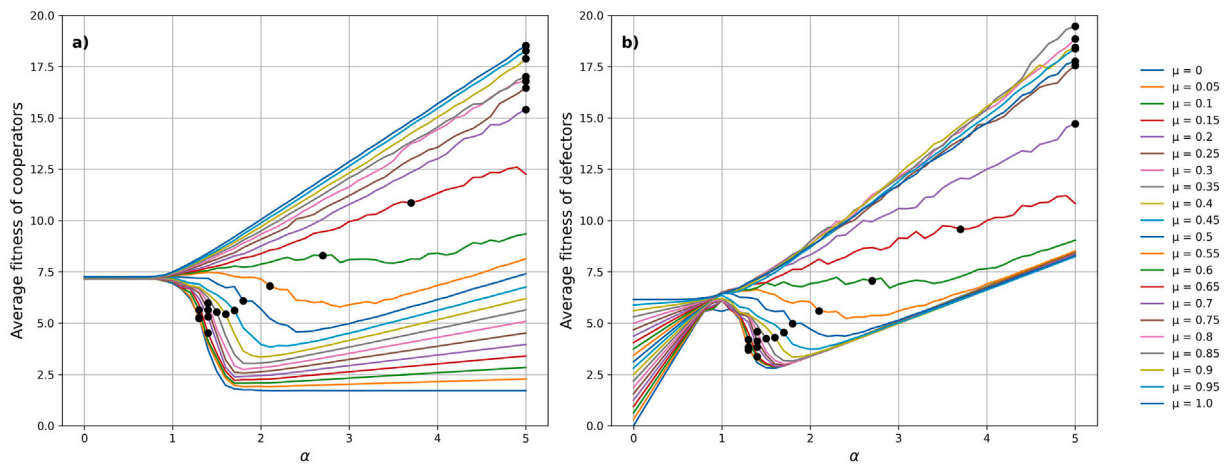


Fig. 6. Average fitness of cooperators and defectors. Average fitness of cooperators (a) and defectors (b) at final time step as a function of α for different values of μ in the BM-Geog scenario. For each μ , we report the corresponding value of α_1 as a black dot.

topology, indicating that long-range shortcuts can limit the persistence of cooperation. This effect is more pronounced in the Siena Model, while in the Basic Model it is weaker. Since the Siena Model relies on a spatial interaction network whose density depends on the choice of the geographical radius, we further checked whether the higher fragility observed in the Siena configurations is robust to changes in this spatial scale. As discussed in Section 2.2.1, the value $r = 100$ m is the smallest radius for which the empirical Siena spatial network remains connected. Therefore, reducing the radius would produce a disconnected network. For this reason, we performed a one-sided sensitivity analysis by increasing the radius by 25% and 50%, corresponding to $r = 125$ m and $r = 150$ m, respectively. These values yield average degrees of approximately $\langle k \rangle \approx 48$ and $\langle k \rangle \approx 64$. For each radius, we recomputed the critical threshold α_1 as a function of μ for both Siena Model configurations, SM-Geog and SM-SW. The results, reported in the Supplementary Material (Fig. S14 and S15), show that the critical thresholds are only weakly affected by the radius for low and intermediate values of μ . In SM-Geog, the values of α_1 remain very similar across $r = 100$, 125, and 150 m up to approximately $\mu = 0.65$. For larger values of μ , sensitivity to the radius becomes more evident: increasing the radius tends to reduce α_1 , meaning that cooperation becomes less robust when agents interact with a larger neighborhood. In SM-SW, the same qualitative pattern is observed, but the effect appears only at higher values of the environmental coupling: the critical thresholds remain almost unchanged up to approximately $\mu = 0.85$, while appreciable differences emerge for $\mu > 0.85$. Overall, this sensitivity analysis indicates that the finding of fragile cooperation in the Siena Model is preserved when the interaction radius is increased above the baseline value $r = 100$ m. Indeed, increasing the interaction radius does not remove this fragility, and the Siena Model remains more fragile than the Basic Model across the explored spatial scales.

To further understand the role of the network structure, we ran an additional experiment in which agents interact on a complete network. Fig. 5 shows that, for almost all values of μ (except $\mu = 1$), the critical threshold α_1 is markedly lower under full connectivity than in the four model configurations considered above. Thus, pushing connectivity to the extreme substantially reduces α_1 , meaning that cooperation collapses already for relatively small defection incentives. This effect can be related to the different network densities considered in the study. The Basic Model networks have an average degree of about $\langle k \rangle \approx 8$, whereas the Siena Model ones are considerably denser, with $\langle k \rangle \approx 35$; the fully connected scenario corresponds to the extreme case $\langle k \rangle = N - 1 = 971$. Consistent with Fig. 5, increasing the average degree across these settings is associated with a lower cooperation level of the system. This pattern is in line with previous results showing that very high connectivity can hinder the persistence of cooperation [53,54]. This observation may help explain why cooperation is comparatively more fragile in the Siena models than in the Basic ones. To disentangle the effect of network density from that of the empirical spatial organization of Siena, we performed a control experiment using a Random Geometric Graph (RGG). The RGG has the same number of nodes as the Siena Model, the same average degree $\langle k \rangle \approx 35$, and the same population composition of behavioral types. However, unlike the empirical Siena network, it does not incorporate the real-world spatial constraints of the historic urban fabric. For each value of μ , we recomputed the critical threshold α_1 and compared the results with those obtained for SM-Geog. The corresponding values are reported in Table S1 in the Supplementary Material. The Random Geometric Graph produces slightly higher α_1 values than SM-Geog for almost all values of μ , except in the high- μ region where both networks reach the upper bound of the explored interval, $\alpha_1 = 5$. Since the two networks have the same number of nodes and the same average degree, this comparison isolates the effect of the empirical spatial organization at fixed network density. The closeness of the two sets of thresholds suggests that a large part of the higher fragility of cooperation in the Siena Model is associated with the higher local connectivity of the spatial network. At the same time, the fact that SM-Geog systematically displays slightly lower thresholds than the Random Geometric Graph indicates that the empirical spatial organization of Siena also contributes to reducing cooperation robustness, although this contribution appears smaller. It is important to note, however, that in real urban systems network density and urban morphology are not fully independent factors [55]. In our spatial construction, the average degree depends on the number of agents located within a given interaction radius. Therefore, in a compact

Table 5

Critical thresholds α_1 in BM-Geog with and without fixed-strategy agents (activists A and deniers D), for different values of the environmental coupling μ .

μ	With A and D	Without A and D
0	$\alpha_1 = 1.31$	$\alpha_1 = 1.41$
0.1	$\alpha_1 = 1.34$	$\alpha_1 = 1.47$
0.2	$\alpha_1 = 1.39$	$\alpha_1 = 1.49$
0.3	$\alpha_1 = 1.45$	$\alpha_1 = 1.51$
0.4	$\alpha_1 = 1.58$	$\alpha_1 = 1.61$
0.5	$\alpha_1 = 1.85$	$\alpha_1 = 1.93$
0.6	$\alpha_1 = 2.66$	$\alpha_1 = 3.35$
0.7	$\alpha_1 = 5$	$\alpha_1 = 5$
0.8	$\alpha_1 = 5$	$\alpha_1 = 5$
0.9	$\alpha_1 = 5$	$\alpha_1 = 5$
1	$\alpha_1 = 5$	$\alpha_1 = 5$

urban fabric characterized by close spatial proximity, narrow streets, and constrained spaces, as in the historic center of Siena, higher local density naturally leads to a higher average degree. In this sense, the higher connectivity of the Siena spatial network should not be interpreted as a property completely separated from urban morphology, but rather as one of the consequences of the compact spatial organization of the city. Overall, this control experiment suggests that the lower robustness of cooperation in the Siena Model is mainly associated with its higher local connectivity, while the empirical spatial organization of Siena provides an additional, although smaller, contribution to cooperation fragility. However, this higher connectivity should also be interpreted as part of the spatial signature of the Siena urban fabric, since the compact morphology of the historic center naturally increases the number of agents falling within a fixed interaction radius.

Moreover, we investigated the role of fixed-strategy agents – activists (always cooperating) and deniers (always defecting) – by repeating the BM-Geog experiments after removing these two groups while keeping all other parameters unchanged. Table 5 shows that removing fixed-strategy agents increases the critical threshold α_1 for low-to-intermediate values of μ (up to $\mu \approx 0.6$ in BM-Geog). Similar qualitative patterns are observed in the other model configurations. For larger μ , the difference vanishes because the system already sustains full cooperation across the explored range of α even in the presence of activists and deniers. Overall, these results indicate that fixed agents can constrain the evolutionary dynamics and reduce the system's ability to self-organize into cooperative configurations, in line with findings on zealot players in spatial Prisoner's Dilemma settings [56,57].

Finally, we investigate the relationship between agents' climate awareness and their cooperative behavior over time by computing, across the whole (μ, α) parameter space, the Spearman correlation between agents' awareness and their cooperation rate at the final time step, defined as the number of time steps in which an agent adopts the cooperative strategy. For each pair (μ, α) , the correlation remains positive, although weak to moderate, with values ranging approximately from 0.14 to 0.29, and is statistically significant for all parameter combinations (p -values $\ll 0.05$). This indicates that more aware agents tend, on average, to cooperate more frequently, while awareness alone does not fully determine behavior. This is consistent with the agent based nature of the model, where individual decisions emerge from the interplay between intrinsic attributes and social interactions. The highest correlations are observed for $\alpha < 1$, i.e., in the regime where cooperation is relatively advantageous. By contrast, when $\alpha > 1$, and defection becomes more rewarding, the awareness-cooperation relationship weakens, suggesting that strong defection incentives can partially override pro-environmental attitudes. However, as μ increases, the correlation between awareness and cooperation becomes stronger even for $\alpha > 1$. This suggests that a stronger influence of the social environment reinforces the alignment between individual attitudes and behavior, allowing more aware agents to sustain cooperative strategies despite unfavorable incentives. As a result, the influence of awareness on cooperative behavior appears partially restored in these regions.

4. Conclusion

The study presented in this paper extends our previous work [28], in which we developed an agent-based model to analyze cooperation dynamics associated with environmental sustainability in the city of Siena, calibrated on empirical data collected through a survey conducted in 2023. In [28], the sample consisted exclusively of $N = 324$ residents of Siena's historic center, and the survey collected individual opinions and practices related to climate change and pro-environmental behaviors. In the present work, we substantially expand the empirical basis through a new 2024 survey ($N = 972$) that includes not only residents of the historic center, but also people living outside the center who regularly visit it for work, study, or other reasons, as well as non-resident students and workers and tourists. This extension reflects the idea that urban sustainability depends on the combined behaviors of those who live in the city and those who frequent it on a daily basis. The 2024 survey results indicate overall high levels of climate-change awareness in the sample, together with generally positive self-reported sustainable practices. At the individual level, awareness and behavior are positively associated but only moderately aligned: higher awareness is, on average, associated with more self-reported pro-environmental practices; however, highly aware individuals do not necessarily report consistently sustainable behavior. This finding is consistent with the well-known knowledge-action gap in pro-environmental behavior [35,36].

The socio-demographic group analysis highlights patterns that are consistent with the literature. First, we observe diverse gender propensities: women report, on average, higher levels of awareness than men, in line with previous studies documenting gender

differences in environmental attitudes and behaviors [50–52]. Second, education displays a marked gradient, with lower values in the middle-school group compared to higher educational levels, consistently with evidence showing that individuals with lower levels of education tend to exhibit lower environmental awareness [58–61]. Third, tourists emerge as the least aware group in the sample. This evidence is plausibly linked to the idea that, during vacations, people tend to partially “suspend” everyday habits and responsibilities and reduce the adoption of pro-environmental practices compared to their home context [62–64]. Finally, we find a difference between residents living outside the historic center and those residing within it, with slightly higher average awareness in the former group. Overall, despite generally high awareness levels, the alignment between attitudes and everyday practices varies across groups; therefore, awareness campaigns and local policies could benefit from a more targeted design that accounts for the socio-demographic differences observed in Siena.

The 2024 survey data were also used to calibrate the agent-based model. Specifically, respondents’ answers were used to classify the $N = 972$ agents into five behavioral types, capturing heterogeneous propensities toward environmental sustainability: 174 activists, 18 deniers, 685 indifferent imitators of the best neighbor, 53 indifferent imitators of the local majority, and 42 indifferent opponents of the local majority. This composition is highly consistent with the distribution obtained in [28] from the 2023 sample of $N = 324$ residents of Siena’s historic center. The ABM developed in this work has enabled a detailed analysis of cooperation dynamics associated with pro-environmental behavior in the city of Siena, using a game-theoretic framework for the decision-making process. In detail, our analysis has focused on the dynamics of cooperation and defection among agents, where cooperation is interpreted as an expression of citizens’ willingness to contribute to environmental preservation, shaped by social interactions and learning mechanisms, whereas defection represents the opposite behavior. We consider two model variants: an idealized Basic Model, based on a regular spatial structure, and an empirically grounded Siena Model, built on the urban geography of Siena’s historic center. For each variant, we analyze two interaction topologies: a geographical network, which captures proximity-based local interactions, and a small-world network, which adds long-range social links to represent non-local social contacts. This yields four configurations allowing us to compare how spatial embedding and network topology jointly affect the diffusion of cooperative sustainable behaviors. We extend our previous work by introducing an environmental-coupling mechanism through a fitness function. In the new formulation, the fitness is a convex combination of the agent’s individual payoff and the performance of the most successful strategy in its neighborhood, with the relative weight controlled by the parameter $\mu \in [0, 1]$. As a result, in both the Basic Model and the Siena Model, and under both the geographical and the small-world network configurations, the system dynamics are shaped by the interplay between the environmental coupling parameter μ and the defection-award parameter α , which is the benefit each player gets from defection.

Our first finding concerns the baseline case $\mu = 0$, where fitness coincides with individual payoff and the model reduces to the framework introduced in our previous work [28], now recalibrated using the 2024 survey data. In this setting, we confirm the main results previously obtained. In particular, for both the Basic Model and the Siena Model, the small-world configuration yields a slightly higher critical threshold α_1 than the corresponding geographical network, indicating that, when $\mu = 0$, the presence of long-range shortcuts may slightly facilitate the persistence of cooperative behavior. At the same time, for a fixed network topology, the Siena Model exhibits systematically lower α_1 values than the Basic Model, confirming that cooperation is more fragile in the empirically grounded Siena interaction structure.

When $\mu > 0$, agents’ fitness also depends on the performance of the locally most successful strategy and, as μ approaches 1, their behavior becomes increasingly shaped by learning from the social context. For each value of $\mu \in [0, 1]$, we compute the critical threshold α_1 in all four model configurations. Our second main result is that, across all configurations, α_1 increases with μ , thereby enlarging the parameter region in which cooperation, and thus environmentally sustainable behavior, prevails. Since α represents the incentive to defect, this finding indicates that stronger coupling to the local social environment makes cooperation more resilient to defection incentives. This effect, however, is not equally strong across all configurations. The increase of α_1 with μ is faster in the Basic Model than in the Siena Model, in both network settings, confirming that the Siena-based interaction structure remains the most fragile with respect to the diffusion of cooperation. Moreover, the effect of the small-world topology is not uniform across the range of μ . For low values of the environmental coupling, the small-world configurations yield α_1 values that are either slightly higher than, or very close to, those of the corresponding geographical networks, suggesting at most a weak positive effect of long-range shortcuts on cooperation. For larger μ , however, this pattern tends to reverse, especially in the Siena Model: α_1 becomes lower under the small-world topology, indicating that long-range shortcuts can limit the persistence of cooperation. This result is consistent with previous studies on spatial Prisoner’s Dilemma dynamics with best-neighbor imitation, in which long-range rewiring was found to increase the vulnerability of cooperative clusters and to facilitate, under some conditions, the spread of defection [65,66].

A third result concerns the role of network connectivity and its relationship with the empirical spatial organization of Siena. The Basic Model and the Siena Model differ not only in their spatial embedding, but also in their average degree: the Basic Model operates on relatively sparse networks ($\langle k \rangle \approx 8$), whereas the Siena-based networks are substantially denser ($\langle k \rangle \approx 35$). This raises the question of whether the lower robustness of cooperation observed in the Siena Model is mainly due to the higher local connectivity of the network. To explore this point, we first considered an extreme case in which agents interact on a fully connected network ($\langle k \rangle = N - 1 = 971$). In this case, the critical threshold α_1 is generally lower than in the other configurations (except at $\mu = 1$), indicating that very high connectivity reduces the robustness of cooperation. This pattern is consistent with the idea that excessively dense interaction structures can weaken the local reinforcement mechanisms that support the persistence of cooperative behavior [53,54]. To disentangle network density from empirical spatial organization, we also compared SM-Geog with a Random Geometric Graph having the same number of nodes, the same average degree, and the same population composition. The two sets of critical thresholds are close, suggesting that the lower cooperation robustness of the Siena Model is largely associated with its higher local connectivity. However, SM-Geog remains slightly more fragile than the Random Geometric Graph, indicating that the

empirical spatial organization of Siena also contributes to reducing cooperation robustness, although to a smaller extent. However, local connectivity and urban morphology should not be interpreted as fully independent factors in real urban systems [55]. For a fixed interaction radius, the number of neighbors depends on how agents are distributed in space; therefore, the compact morphology of Siena's historic center naturally increases the number of agents located within local interaction neighborhoods. In this sense, the higher average degree of the Siena-based network can itself be understood as one structural consequence of the compact spatial organization of the city. Overall, our findings suggest that denser social interaction structures do not automatically imply stronger cooperation and may instead be associated with more fragile cooperative dynamics.

A further result concerns the role of fixed-strategy agents in the model, namely activists and deniers. We found that, for low-to-intermediate values of μ , removing fixed-strategy agents increases the critical threshold α_1 , meaning that cooperation remains prevalent under stronger incentives to defect. For larger μ , this difference disappears because the system already reaches full cooperation across the explored α -range. Overall, this result indicates that non-updating agents affect the collective dynamics and may limit the system's ability to self-organize into more cooperative configurations. This is broadly consistent with previous work showing that zealot players can hinder cooperation dynamics in spatial social dilemmas [56,57].

Finally, we analyze the relationship between agents' climate awareness and their cooperative behavior, finding a positive but weak to moderate correlation across the (μ, α) parameter space. This indicates that more aware agents tend, on average, to cooperate more frequently over time, although awareness alone does not fully determine behavior. Together with the moderate empirical correlation between awareness and self-reported sustainable behavior, this result supports the use of an agent-based modeling framework: sustainable behavior cannot be explained by awareness alone, but must be studied as the outcome of the interplay between individual attributes, strategic incentives, network structure, and social-interaction mechanisms.

While the proposed framework provides useful insights, several limitations should be acknowledged. First, socio-demographic characteristics, such as age, gender, education, and residency status, are used only to describe variation across socio-demographic groups in the survey results and do not explicitly affect agents' decision-making in the model. A natural extension would be to incorporate socio-demographic heterogeneity directly into behavioral dynamics. Second, climate-change awareness is treated as a fixed individual attribute throughout the simulations. This is a simplifying assumption, since awareness may evolve over time through social interactions. Extending the model to include a dynamic awareness variable would allow us to study the co-evolution of awareness and behavior. A third limitation concerns the mapping between the survey-based behavioral orientations elicited by question Q9 and the game-theoretic player types assigned to indifferent agents. Although Q9 was designed to capture attitudes toward social influence in a socially visible and locally regulated behavior such as waste sorting, the correspondence between these responses and the PD, SH, and HD updating rules is a modeling assumption. A direct empirical validation of this mapping would require dedicated behavioral data, for example from experimental settings or observations of respondents' reactions to neighbors' behavior. This assumption may limit the ability of the model to predict specific environmental behaviors; however, cooperation in the model is interpreted as a broader simulated pro-environmental orientation, so the resulting dynamics remain meaningful for studying collective behavior under social interaction and learning. Fourth, in this work we consider only two network topologies for both model variants: a geographical network based on spatial proximity and a small-world network. Future work could explore additional interaction structures and more realistic social networks, for example by distinguishing ties related to neighborhood, friendship, or work/study contexts. Finally, the present analysis is case-study-specific and focuses on Siena. Testing the same framework in other urban contexts, including cities with spatial structures similar to Siena and cities with more regular urban layouts, would help assess the robustness and generalizability of the results.

CRediT authorship contribution statement

Vittoria Socci: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Chiara Mocenni:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

This appendix provides the full survey questionnaire distributed in 2024, from which we collected 972 responses from residents and non-residents of Siena (Italy) for our analysis.

Table A.1
2024 Survey.

S.1	Q.1 How much do you agree or disagree with the following statements on a scale from 0 to 10, where 0 means “completely disagree” and 10 means “completely agree”?
	Q1.1 Our daily choices can significantly affect the global environmental impact.
	Q1.2 Climate change can significantly affect desertification and water resource availability.
	Q1.3 Climate change and its consequences, such as rising temperatures and extreme weather events, can significantly influence our physical, psychological, and social well-being.
	Q1.4 The current global climate crisis is a direct consequence of human activities.
	Q1.5 The consequences of climate change have changed or will change our lifestyle and consumption habits.
	Q1.6 The climate change we are observing is not only a natural process.
	Q.2 How often do you try to reduce energy and water consumption in your daily activities (e.g., showering, using appliances, lighting rooms)?
	(a) Always (b) Almost always (c) Sometimes (d) Almost never (e) Never
	Q.3 Do you participate in the waste sorting organized by the Municipality of Siena?
	(a) Always (b) Almost always (c) Sometimes (d) Almost never (e) Never
	Q.4 How often do you reuse materials such as paper, plastic, or glass?
	(a) Always (b) Almost always (c) Sometimes (d) Almost never (e) Never
	Q.5 How often do you dispose of hazardous waste (batteries, expired medicines, used oil, etc.) properly?
	(a) Always (b) Almost always (c) Sometimes (d) Almost never (e) Never
	Q.6 How attentive are you to the environmental impact of your purchases (food, clothing, cars, etc.)?
	(a) Very much (b) A lot (c) Fairly (d) A little (e) Not at all
	Q.7 Have you ever participated in cleaning public places (e.g., parks, beaches, squares)?
	(a) Yes, once or more times.
	(b) No, but I might decide to if the opportunity arises.
	(c) No, I don't think it is useful.
S.2	Q.8 Have you ever considered using technologies that reduce environmental impact (e.g., electric cars, low-emission heating)?
	(a) Yes, I have done so recently.
	(b) No, but I might consider it in the future.
	(c) No, I'm not interested.
	Q.9 How do you approach waste sorting compared to your neighbors?
	(a) I tend to follow the waste-sorting practices adopted by most of my neighbors.
	(b) I tend to behave differently from most of my neighbors.
	(c) In general, I try to follow the waste-sorting guidelines provided by public authorities.
	Q.10 In your opinion, for each of the following materials, do your neighbors sort their waste correctly?
	Q10.1 Paper: (a) Yes, always (b) Yes, most of the time (c) No, almost never (d) No, never
	Q10.2 Multi-material: (a) Yes, always (b) Yes, most of the time (c) No, almost never (d) No, never
	Q10.3 Organic waste: (a) Yes, always (b) Yes, most of the time (c) No, almost never (d) No, never
	Q10.4 Hazardous waste: (a) Yes, always (b) Yes, most of the time (c) No, almost never (d) No, never
	Q10.5 Bulky waste: (a) Yes, always (b) Yes, most of the time (c) No, almost never (d) No, never
	Q.11 What is the most accurate definition of “climate change”?
	(a) A change in the average conditions of the entire Earth's climate system observed over a long period of time.
	(b) A sudden change in local atmospheric conditions observed over a short period of time.
	(c) I don't know.
	Q.12 What does “mitigation of climate change” mean?
	(a) Acting on the consequences of climate change by alleviating its impacts on the environment and socio-economic sectors.
	(b) Acting on the causes of climate change by reducing human-generated greenhouse gas emissions.
	(c) I don't know.
	Q.13 What does “adaptation to climate change” mean?
	(a) Acting on the consequences of climate change by trying to limit and manage the impacts and risks for the environment and socio-economic sectors.
	(b) Getting used to the unavoidable consequences of climate change impacts on the environment and socio-economic sectors.
	(c) I don't know.
	Q.14 By how many degrees has the global average temperature increased since pre-industrial levels?
	(a) By about 1 °C.
	(b) By about 1.5 °C.
	(c) I don't know.

(continued on next page)

Table A.1 (continued).

Q.15 By how much has the global sea level risen since the pre-industrial period?

- (a) By about 10 cm.
- (b) By about 20 cm.
- (c) I don't know.

Q.16 Please indicate your status in Siena as:

- (a) Resident
- (b) Non-resident worker
- (c) Non-resident student
- (d) Tourist
- (e) Occasional visitor

Q.17 Age:

- (a) 14-23
- (b) 24-33
- (c) 34-43
- (d) 44-53
- (e) 54-63
- (f) 64-73
- (g) 74+
- (h) Prefer not to say

Q.18 Gender:

- (a) Female
- (b) Male
- (c) Non-binary
- (d) Prefer not to say

Q.19 Educational level:

- (a) None
- (b) Primary school certificate
- (c) Middle school certificate
- (d) High school diploma
- (e) Bachelor's degree
- (f) Master's degree
- (g) Postgraduate Master's degree
- (h) PhD
- (i) Prefer not to say

Q.20 Employment status:

- (a) Employed
- (b) Unemployed
- (c) Retired
- (d) Student
- (e) Other
- (f) Prefer not to say

Q.21 Do you live (even temporarily) in Siena's historic center?:

- (a) Yes [go to Q.22]
- (b) No [go to Q.25]

Q.22 Select the street in the historic center where you live or stay:

- (a) Select a street [go to Q.24]
- (b) Prefer not to say [go to Q.23]

Q.23 If you did not answer the previous question, indicate the district ("Terzo") of Siena where you live or stay:

- (a) Terzo di Città
- (b) Terzo di Camollia
- (c) Terzo di San Martino

Q.24 In addition to the street where you live or stay, indicate the other street in the historic center that you visit most frequently (for work, study, free time, religion, etc.):

- (a) Select a street [go to Q.26]
- (b) Prefer not to say [go to Q.26]

Q.25 If you do not live in the historic center, indicate the street you visit most frequently (for work, study, free time, religion, etc.):

- (a) Select a street [go to Q.26]
- (b) Prefer not to say [go to Q.26]

Q.26 Indicate the income range that best represents your household's monthly net income:

- (a) 0-1999€
- (b) 2000-3999€
- (c) 4000€ and above
- (d) Prefer not to say

S.3

Appendix B. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.chaos.2026.118852>.

Data availability

The data supporting this study are available at <https://github.com/vittoriasocci/MAS.git>.

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