



An agent-based model to foster citizens' sustainable behavior in the Italian city of Siena

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Abstract. Climate change is irreversibly having an increasing impact on the environment, people and the economy worldwide. The contribution of each individual in counteracting its effects is crucial, as everyday actions, from a proper participation in waste sorting to responsible consumption choices, can shape a more resilient and environmentally friendly future. How much do the geographical and urban features of an Italian art city impact the spread of sustainable behaviors among its citizens? In this paper, we investigate the climate awareness and attitudes toward sustainability of citizens living in the historical center of Siena, a small art city among the most sustainable in Italy. Using a geo-referenced agent-based model (ABM) and game theory for the human decision-making process, we simulate how pro-environmental attitudes spread in a population of predominantly selfish individuals and in which there are also herding and anti-herding mechanisms. We claim that on the one hand, the conformation and geographical position of the city of Siena make it naturally sustainable, but at the same time its urban structure and connection networks seem to limit the spread of cooperative actions toward environmental protection.

1 Introduction

Climate change is one of the most urgent global challenges facing humanity today. Its consequences are increasingly evident, from rising global temperatures to the frequency and intensity of extreme weather events.

Human activities, in particular the emission of greenhouse gases from the burning of fossil fuels and deforestation, have contributed significantly to this phenomenon [1]. In fact, humans affect the global climate mainly through changes in atmospheric composition and by emissions of greenhouse gases such as carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O) and others, causing global warming [2]. Compared to preindustrial levels, the average temperature of the planet has increased by about 1 °C (1.8 °F), mainly due to anthropic practices [1].

One of the human activities that contributes strongly to greenhouse gas emissions is the waste sector, which is one of the main methane emitting sectors and is responsible for about 20% of global anthropogenic methane

(CH₄) emissions [3]. In the short term, methane (CH₄) is more than 80 times more damaging than carbon dioxide (CO₂) as a climate pollutant and it is responsible for almost half of the 1 °C warming recorded so far [4].

Global warming is accompanied by a number of effects, such as warming of the oceans, rising sea levels, reduction in the extent of Arctic sea ice, higher frequency and intensity of heat waves, intensification of extreme weather events such as heavy precipitation, increased frequency of floods, tornadoes and hurricanes, worsening droughts, and many other effects [1, 5–7], which not only cause significant loss of life, but also substantial economic damages by harming buildings and infrastructure, impacting sectors including agriculture, construction, transportation, manufacturing and tourism [8]. Such phenomena are increasingly common in many countries around the world.

In 2023 in the north-central area of the Tuscany region, particularly in many areas bordering the city of Florence, nearly 200 mm of rain fell in 3 h [9] causing a disastrous flood with eight deaths and subsequent economic damages amounting to nearly 1.9 billion euros in total [10]. Moreover, the increased concentration of carbon dioxide (CO₂) in the atmosphere due to greenhouse gas emissions caused by human activity can significantly alter terrestrial and marine ecosystems worldwide [7]. Thus, it is clear that climate change, with all its consequences, is a real and urgent problem that all humanity must face.

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Tackling climate change requires a global response and a joint effort by governments, institutions, companies, stakeholders and local authorities. In this sense, governments must develop sound policies and regulations to promote sustainable practices in all sectors having an environmental impact. They can also educate and raise public awareness about the importance of sustainable behavior. Local authorities, on the other hand, play a crucial role in implementing government policies and regulations at the local level, in day-to-day management.

What is the role of citizens and their knowledge, opinions, awareness and experience on climate change effects in this context? To be effective, joint actions of governments and local authorities must be supported by the population. Active participation of citizens in making responsible consumption choices, such as waste reduction, helps to reduce greenhouse gas emissions in such a way as to decrease the overall environmental impact on climate.

In this paper, therefore, the focus is on the role single individuals play in this context, seeking to foster sustainable behaviors among them with the final aim of reducing the environmental impact of human activity on the climate.

Agent-based models (ABMs) are particularly suitable in modeling environmental attitudes among people, as they represent complex systems where agents are autonomous entities interacting with each other and the environment [11]. ABMs have been widely applied to sociology and have been powerful tools for examining agent-agent interaction and understanding how individual actions influence social outcomes, as analyzed by the authors of [12]. This encourages the use of such models in the context of environmental sustainability, allowing to analyze how agent-agent and agent-environment interactions at the micro-level may or may not give rise to sustainable scenarios at the macro-level.

In this work, we propose an ABM where the entities of the model are citizens, with the aim of promoting sustainable behaviors at the individual level and assessing the global environmental impact of human activity on climate change. We chose as case study the City of Siena (Tuscany, Italy), which is recognized as one of the most sustainable medieval cities of art in Italy for its quality of life, reduced industrial activity, low air and water pollution, and carbon neutrality goal since 2011 [13]. For these reasons, Siena is an ideal example for studying sustainable behaviors arising spontaneously and without necessity or legal obligations in a population, thus highlighting how local efforts may or may not contribute to collectively facing climate change damages.

By means of a survey administered to the population living in the historical center of Siena from May to July 2023, we collected their opinions on climate change and their propensities toward sustainable practices in different aspects such as waste sorting and recycling, cleaning public spaces, food and good purchases. The new obtained dataset is used to tune the model.

The main objective of the study is developing a model to investigate the evolution of citizens' behavior over time, faithfully representing the human decision-making (DM) through the ABM. This priority stems from the recognition that facing climate change requires pro-environmental actions of any single individual [14]. Moreover, in agreement with the results presented in [15] where a social-ecological ABM on water use has been proposed, the patterns emerging at the macro-level depend on how people make decisions at the micro-level.

Game theory (GT) and evolutionary game theory (EGT) have been recognized to be particularly suitable in modeling DM processes [16, 17], especially for the study of social interactions among rational individuals whose decisions are interdependent [18]. EGT is an application of GT combining the principles of biological evolution with the analysis of strategic interactions and aims to understand how behavioral strategies evolve over time in a population context in which individuals interact repeatedly [17]. Therefore, GT and EGT are particularly fit for our purpose, allowing to analyze how sustainable behaviors spread among citizens and last over time. A huge amount of literature has been devoted to model sustainable behaviors by means of public good games, where individuals cooperate for a common good, thus ensuring environmental preservation [19–21]. Cooperation has been widely formulated and analyzed in the context of EGT [22]. For example, the prisoner's dilemma (PD) game has been employed as a metaphor for examining cooperation among selfish individuals [23], while the stag-hunt (SH) and hawk and dove (HD) games represent herding and anti-herding mechanism, respectively [24, 25].

In this work we examine how cooperation, defined as the promotion of sustainable behaviors, spreads among residents of Siena's historic center, which are assumed to be mostly (PD) players. To better represent heterogeneity within a population, we have included also (SH), (HD), and special players, where the latter are assumed to have fixed strategies.

We found valuable results from the new survey, specifically designed for this research, revealing correspondences between different citizens' attitudes toward sustainable practices and the specific games considered in this study. For the first time, to the best of our knowledge, a survey focused on individual environmental behaviors in the Italian city of Siena has been developed by engaging a significant sample of the population. The obtained results confirm the gap in climate awareness related to the educational level [26–33] and the phenomenon known as the eco-gender gap [34–36]. Surprisingly, however, they indicate that the youngest age class is not the most aware of climate change [26, 37]. The obtained dataset has been not only analyzed from a statistical point of view, but also used to tune our ABM on real and local data.

The simulations achieved with the developed ABM allow to evaluate how cooperation among citizens toward sustainability spread in the small Italian city of Siena. The exploration of different scenarios unex-

Table 1 Survey on environmental behaviors for the inhabitants of the historical center of Siena

S.A	Q.1 Age Q.2 Gender Q.3 Educational level Q.4 “Terzo” of Siena where you live Q.5 Address where you live
S.B	Q.6 In your opinion, how much can your daily choices influence the global impact on the environment? Q.7 How often do you try to reduce energy and water consumption? Q.8 Do you participate in the waste sorting organized by your municipality correctly? Q.9 How often do you recycle products (paper and cardboard, organic, plastic, glass, etc.) at home? Q.10 How often do you correctly dispose of special dangerous waste (batteries, expired medicines, etc.)? Q.11 When dealing with waste sorting, what is your main approach? Q.12 Have you ever participated in cleaning public places such as beaches, seafronts, parks, squares? Q.13 How careful are you about the environmental impact of your purchases (food, cars, clothings, etc.)? Q.14 What is your approach toward waste sorting in relation to the behavior of others?

pectedly seemed to suggest that the geographical and urbanistic features of the city itself may have a significant impact on this phenomenon.

The paper is organized as follows: in Sect. 2, the dataset obtained from the survey and methods applied in the study is presented, providing an overview of ABMs and the use of GT and EGT for representing the human DM process. Section 3 is devoted to the survey results, used to tune the model, and to the implementation and development of our ABM. In Sect. 4, we investigate the results obtained from the ABM and, finally, in Sect. 5 we provide the most relevant conclusions and future research directions. Furthermore, in the supplementary material we report the full survey and the complete description of our ABM using the standard “Overview, Design Concept and Details” (ODD) protocol widely used by agent modelers and introduced by Grimm et al. [11].

2 Material and methods

The dataset used in this study has been obtained by conducting a survey among citizens living in the historic center of Siena from the mid of May to the end of July 2023, mainly using social networks. The distribution of the survey resulted in the collection of 324 responses, representing a sample of the whole population taken into consideration and consisting of the agents of our model. The survey is organized in two sections, which are reported in Table 1 together with the corresponding questions.

Section A (S.A) is aimed at collecting the respondents’ anagraphical data to understand the composition and characteristics of the sample. This part is composed of five questions in which we ask the interviewees their age, gender, educational level, address (without house number) and the area of the historic center of Siena in which they live. Specifically, the city of Siena has been historically subdivided into three neighbourhood within the medieval walls, hereafter called “Terzi”: the “Terzo di Città” (C), the “Terzo di Camollia” (CM) and

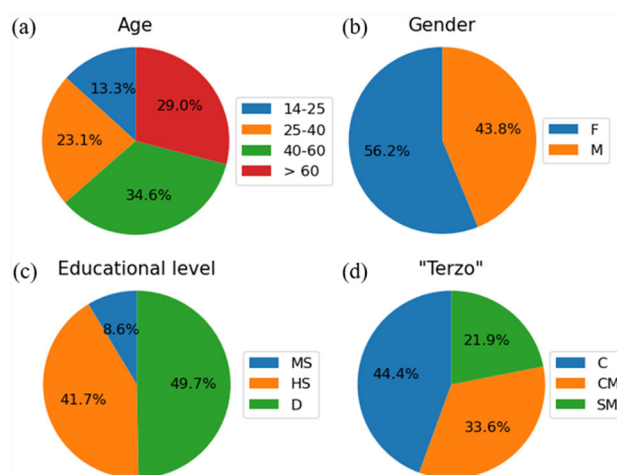


Fig. 1 **a** Percentages of respondents belonging to the four age categories 14–25, 25–40, 40–60 and over 60 years. **b** Percentages of respondents belonging to the two gender categories F and M. **c** Percentages of respondents belonging to the three educational level categories: middle school (MS), high school (HS) and degree (D). **d** Percentages of respondents belonging to the three historical “Terzi” subdividing the city of Siena: “Terzo di Città” (C), “Terzo di Camollia” (CM) and “Terzo di San Martino” (SM)

the “Terzo di San Martino” (SM). This division jointly with the address allows us to geo-reference the citizens as it will be described in details below. Section A of Table 1 is well represented by the pie charts in Fig. 1, where the percentages of respondents belonging to each age, gender, educational level and “Terzo” category are shown.

The two largest age classes are the 40–60 and over 60 years, representing 34.6% and 29% of the sample, respectively. The 25–40 age category accounts for 23.1% of the sample, and the 14–25 category, which is the smallest, accounts for 13.3% of the sample. Citizens who participated in the survey were predominantly women (F), accounting for 56.2% compared to 43.8% of men (M). The largest educational category is composed of

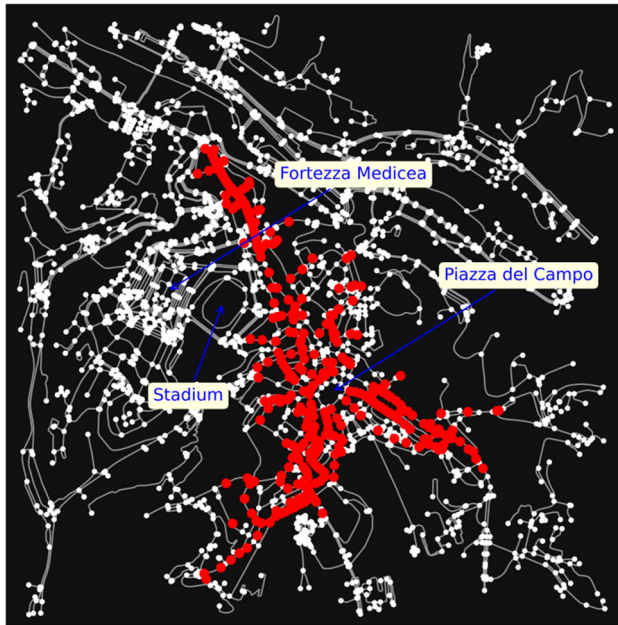


Fig. 2 Geo-referencing agents on the map of Siena

citizens owning a degree (D), followed by people with a high school (HS) and a middle school (MS) diploma, representing the 49.7%, 41.7%, and 8.6% of the sample, respectively. Finally, 44.4% of the respondents live in the “Terzo” (C), 33.6% in the “Terzo” (CM), and 21.9% in the “Terzo” (SM).

This distribution in the three “Terzi” along with the address allows us to give a position to each of the respondent on the map of Siena, enabling to geographically visualize the answers. To this aim we have first built the map of the city by means of the python OSMnx library [38] which transforms the OpenStreetMap into a graph. The white dots represent the intersections between roads, while the links are the streets connecting them, as shown in Fig. 2. In detail, the map has been generated by setting as central point the geographical coordinates of the official headquarters of Banca Monte dei Paschi di Siena (Piazza Salimbeni) and a radius of 1200 m. The result is a map in which key elements of the historic city center of Siena, such as the Piazza del Campo, the stadium and the Fortezza Medicea, are clearly visible. Furthermore, the 324 respondents of the survey are indicated by the red dots present on the map shown in Fig. 2, allowing us to verify that the respondent sample approximately covers the entire historic center.

Section B (S.B) contains nine questions on citizens’ environmental habits, allowing to estimate their climate awareness level and to identify several types of agents according to their attitudes toward sustainable practices, which are the following:

- **Activists:** people strongly involved in environmental problems and in actively fighting climate change.
- **Deniers:** people not involved in behaviors contrasting climate change, potentially taking actions dam-

aging the environment or believing that it is not a real and urgent problem.

- **Indifferents:** people characterized by indifference toward environmental problems. Among them, we have identified three different types, specifically (i) the *indifferent imitators of the majority of neighbors*, (ii) the *indifferent opponents of the majority of neighbors* and (iii) the *indifferent imitators of the best neighbor*.

This classification will be used to define the different games embedded in the mathematical model.

2.1 Agent-based modeling

Agent-based modeling is a computational modeling technique used to study the collective behavior of complex systems, such as groups of individuals or autonomous decision-making (DM) agents interacting with each other and their environment. An agent-based model (ABM) is thus a particular type of model where agents are represented as autonomous and unique entities endowed with certain attributes and make decisions on some issue according to a set of rules. The agents of an ABM generally exhibit adaptive behavior, since they regulate their behavior and decisions according to their current states, those of other agents and of the environment. Hence, in agent-based modeling, instead of describing a system from a macroscopic level as we do with approaches using differential equations, we describe the system from a microscopic level by defining its individual agents in a bottom-up approach [11, 12, 39, 40]. Consequently, an ABM allows both to understand how a system’s behavior at the macroscopic level derives from the behaviors of individual agents at the microscopic level and to grasp how the behaviors of individual agents are affected by the behavior of the system as a whole.

The main benefit of agent-based modeling is to be able to capture emergent phenomena resulting from the interactions of individual entities with each other and with the environment [39]. Very often the patterns emerging at the macro-level depend on how individuals make decisions at the micro-level [15]. Therefore, representing human DM, which can be defined as the cognitive process of making a choice from a number of alternative actions [41], in ABMs is of primary importance.

The DM process can be described in many ways, depending on the context and the considered application. In [42] the authors provide an overview of some of the ways in which decisions can be embedded in ABMs: from the use of simple logical rules (if-then) to more sophisticated neural networks and genetic algorithms. In [43] the focus of the study is, in particular, on DM approaches based on Markov Decision Processes. The researches developed in [16, 17, 44] deal with DM processes described by game theory (GT) and evolutionary game theory (EGT).

2.2 Game theory

GT is a mathematical field dedicated to the study of social interactions between rational individuals whose decisions are interdependent, that is, the outcome of their choices depends not only on their own decisions but also on those of all the others [18]. In this section, we briefly explain the games considered in our study, pointing out that for each of them we consider iterated versions with multiple players and rounds.

The prisoner's dilemma (PD) game was first formulated in 1950 by mathematicians Merrill M. Flood and Melvin Dresher at the Rand Corporation in the United States [45]. Later, Albert W. Tucker formalized the game as we know it today and gave it the name "prisoner's dilemma" [46]. The dilemma can be described as in [47] where two suspects, accused of committing a crime, are arrested by the police and locked in two different cells preventing them from communicating. Both are given two choices: confess or remain silent. If both confess, the total number of years in jail will be higher than when both choose to remain silent. If one confesses and the other remains silent, the confessor gains a personal benefit by being freed from all charges, while the other will receive a more severe sentence than if both would have chosen to stay quiet. The two pure strategies "confess" and "remain silent" of the game can be renamed as "defection" and "cooperation", respectively. The "confession" is often interpreted as an action of defection, in which one prisoner betrays the other by collaborating with the prosecution, gaining a personal benefit at the expense of the other. On the other hand, "remaining silent" can be interpreted as a cooperative action in which one prisoner chooses not to betray the other, forgoing a personal advantage and preserving a better outcome for both. Paradoxically, rational logic drives both suspects to confess, being the more individually convenient option, even if this choice leads to a more socially disadvantageous outcome than if both had remained silent. This implies that there is only one pure Nash equilibrium in the game which is given by the pair (confess, confess). In the non-iterated version of the PD game as the one just described, the two criminals never have to work together again. They both reason in the manner described above and therefore decide to confess (defection). In our work, however, we consider an iterated version of the PD with more than two players and multiple rounds. In this version the scoring is different, and is computed as in [47]: the basic hypothesis is that an increase in the number of people cooperating proportionally raises the benefit for each of them. This assumption suggests that cooperation may lead to greater individual reward, thus encouraging players to cooperate with each other. For players who defect, their benefit is assumed to be given by an α factor multiplied by the number of people who cooperate, where the parameter $\alpha \in [0, 3]$ represents the benefit each player obtains from defection and it is called *defection award*. This may reflect situations in which non-cooperators benefit from the actions of cooperators without contributing to the common good.

Table 2 PD game bi-matrix

P1/P2	C	D
C	(1,1)	(0, α)
D	(α ,0)	(0,0)

The stag-hunt (SH) game was first introduced by philosopher and mathematician Jean-Jacques Rousseau in his book "Discourse on the Origin and Foundations of Inequality among Men" (1755) [18]. Rousseau used this game to discuss the concept of social cooperation and the dilemma between self-interest and collective ones. The game can be described imagining two hunters facing a dilemma: they go hunting and must decide whether to hunt a stag or a hare. Their decision has to be made without knowing the decision of others, and keeping in mind that to hunt a stag successfully both of them must cooperate, while for the hare the efforts of a single person are sufficient. Therefore, each player can choose between two pure strategies: "Stag" and "Hare", which can be renamed as "cooperation" and "defection", respectively. Each player will choose the Stag strategy when also the other will choose the same and likewise for the Hare strategy, depicting a herding mechanism and resulting in two pure Nash equilibria: (Stag, Stag) and (Hare, Hare).

The hawk and dove (HD) game was introduced by biologist John Maynard Smith and geneticist George Price in 1973 in their paper "The logic of animal conflict" [48]. This game captures a basic feature of animal conflict and can be used to analyze strategic behaviors between individuals in situations of conflict and cooperation, as in the previous two cases. The game is defined by imagining two animals fighting for a limited resource of food and having two possible strategies: "Hawk" and "Dove". The Hawk strategy is more aggressive and violent and can be interpreted as "defection", while the Dove one is more passive and docile and can be seen as "cooperation". If both players choose the Hawk strategy, they will fight until one is defeated and the other wins the resource, while if both players choose the Dove strategy, they will avoid the fight and will share the resource. Finally, if one player chooses the Hawk strategy and the other the Dove one, then the former will get the entire food resource for himself, while the latter will flee. In this context, each player will prefer to have an aggressive strategy when the other is more docile and vice versa, representing an anti-herding mechanism and giving rise to only the Nash equilibrium: (Hawk, Dove).

For the three games introduced above, renaming the strategies as "cooperation" (C) and "defection" (D), we get the bimatrices shown in Tables 2, 3 and 4, where $(x, y) = (\text{score of player 1, score of player 2})$.

We also consider two other games having two fixed strategies, (C) and (D), which are again regarded in their iterated versions with multiple players and rounds. In the former one the player chooses at each iteration the (C) strategy, while in the latter the player's choice always falls on the (D) strategy.

Table 3 SH game bi-matrix

P1/P2	C	D
C	(1,1)	(0,0)
D	(0,0)	(1,1)

Table 4 HD game bi-matrix

P1/P2	C	D
C	(0,0)	(1,1)
D	(1,1)	(0,0)

2.3 Embedding game theory in ABMs

A huge amount of literature proves the widespread use of GT and EGT to represent the DM process in ABMs in many fields [16, 17, 44, 49–51]. EGT originated as an extension of GT to theoretical biology to study the strategic behavior of animals, particularly in the context of the evolution of competition and cooperation strategies [48, 52]. Over time, EGT has expanded beyond the field of biology and found application in many other disciplines, such as economics, psychology, sociology, computer science and political science [17].

In all cases, EGT can be used to model DM processes when agents interact in situations of conflict or cooperation and provides a theoretical framework for understanding how behavioral strategies evolve over time in a population. Cooperation is a central concept in EGT and can be defined as the propensity of individuals to collaborate for mutual benefits, despite the possibility of acting selfishly [53]. EGT investigates how such cooperative behaviors can evolve and persist over time in the population under consideration.

Cooperation among individuals emerges as a key element in fighting climate change and promoting environmental sustainability. Climate awareness, sustainable behaviors and collaboration are essential to mitigate negative impacts on the environment, thus transforming individual cooperation into a unifying force for the preservation of our planet [54, 55].

For this reason, since the operational objective of this research is to develop an ABM where the entities are citizens living in the historical center of Siena, to foster sustainable behaviors among them and consequently to observe the emergence of cooperation, we decided to use GT and EGT to describe the DM process embedded in the model.

This choice implies that each agent in our model is a player able to select, regardless of the game in which he participates, between two pure strategies: cooperation and defection, where cooperation represents the ensemble of sustainable actions from an environmental point of view and vice versa for defection.

The five agent types identified through the survey correspond to the five different games explained in Sect. 2.2, as shown in Table 5, which are thus the games embedded in our ABM and of which we consider iter-

Table 5 Correspondence between agent types and games

Agent type	Game
Activist	C
Denier	D
Indifferent imitator of the best neighbor	PD
Indifferent imitator of the majority of neighbors	SH
Indifferent opponent of the majority of neighbors	HD

ated versions with multiple players and rounds to analyze the spread of cooperative behavior in the population.

The indifferent imitators of the best neighbor, the majority of neighbors and the opponents of the majority of neighbors correspond to prisoner's dilemma (PD), stag-hunt (SH) and hawk and dove (HD) players, respectively, and can change strategy at each iteration of the model. Conversely, activists (A) and deniers (D) always choose the same strategy at each time instant: cooperation for the former and defection for the latter.

3 Developing the geo-referenced ABM for environmental sustainability

This section is devoted to the implementation of our ABM, which takes inspiration from an existing model [47], exploring how the behavior of agents positioned on a grid evolves as they play iterated (PD) with their neighbors.

Our model includes also (SH), (HD), and special players with fixed strategies and has been developed using Netlogo (version 6.3.0) [56], which is a model programming environment for the simulation of social and natural phenomena and it is particularly suitable for modeling complex systems evolving over time. Since the dataset obtained from the survey is used to initialize our model, we report in the following section its results, which enabled us both to assess the climate awareness of the examined population and to determine the number of agents in the sample belonging to each of the five categories (A), (D), (PD), (SH) and (HD). Finally, in Sect. 3.2, we explain the model implementation.

3.1 Survey results and climate awareness

The climate awareness level of each respondent is estimated using question 6 of the survey (hereafter referred to as Q.6), asking each citizen how much he thinks his daily choices can influence the global impact on the environment. Respondents can choose, as an answer, a numerical option from 1 to 10, where 1 means a total lack of awareness and vice versa for 10. Figure 3 reports the bar diagrams related to the climate awareness level for each of the age, gender, educational level and "Terzo" categories considered in the survey, where data have been normalized for a better comparison. Furthermore, Fig. 4 shows the same bar diagrams where

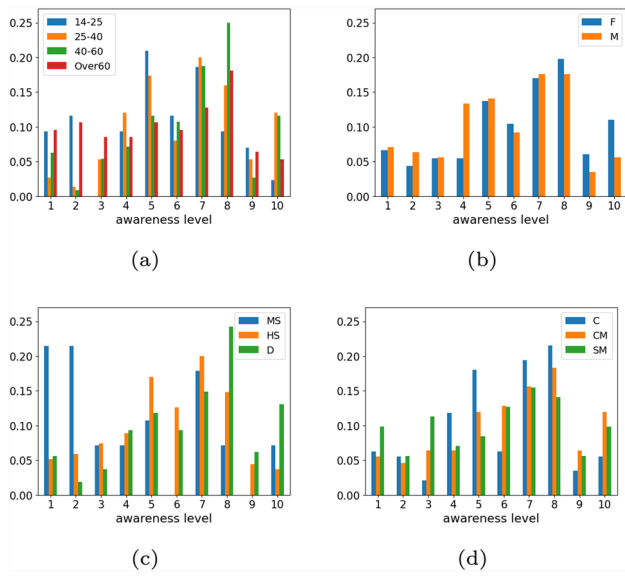


Fig. 3 Bar diagrams illustrating the awareness level for **a** age, **b** gender, **c** educational level, **d** “Terzo”

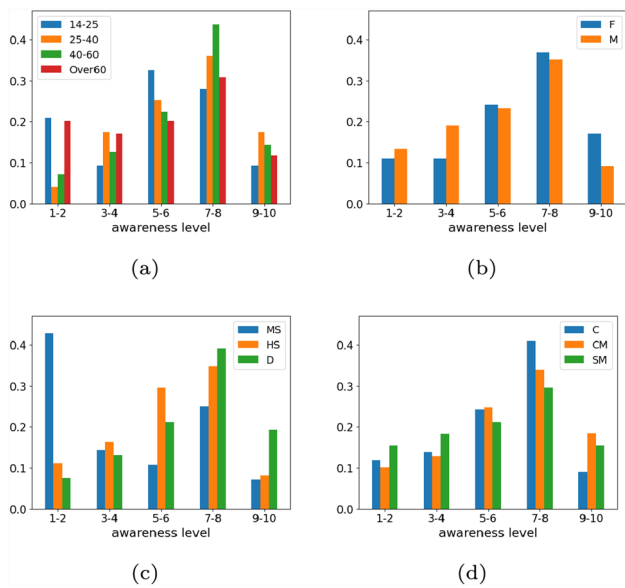


Fig. 4 Condensed bar diagrams illustrating the awareness level for **a** age, **b** gender, **c** educational level, **d** “Terzo”

the numerical options are combined in pairs for a more accurate analysis.

Figure 3a shows that the 40–60 age category is the most aware about climate change, presenting a bell-like pattern with a very high peak shifted to the right on numerical option 8. Next we have the 25–40 age group, again showing a bell-like pattern with a peak on numerical option 7 and a slightly lower one on numerical option 5. The youngest age category 14–25 shows a lower awareness than the previous two, always presenting a bell-like pattern but with its highest peak on numerical option 5. Finally, we have the over 60 years age class which is the least aware. Even though it

shows its highest peak on numerical option 8, the previous options turn out to be chosen by a more or less constant number of over 60 respondents and the two highest options (9 and 10) are chosen by a much lower number of them. Condensing together the numerical options into pairs, as in Fig. 4a, the analysis is confirmed.

Figure 3b shows how the female category is slightly more aware than the male one. The women’s class exhibits much higher peaks than men on the largest numerical choices 8, 9 and 10 and much lower peaks than men on the smaller numerical choices 1, 2, 3 and 4, while on choices 5, 6 and 7 the peaks are more or less similar. Again, putting together the numerical options into pairs, as in Fig. 4b, the analysis is confirmed.

Figure 3c shows how the category owning a degree (D) is definitely the most aware, presenting much higher peaks on the greater numerical options 8, 9 and 10 and lower peaks on almost all the other numerical options with respect to the other two groups. The category possessing a high school (HS) diploma still presents a fairly high level of awareness, though less than the degree group. Finally, the category with a middle school (MS) diploma is clearly the least aware, showing very high peaks on the smallest numerical options 1 and 2. The analysis is confirmed by the pair-grouped data reported in Fig. 4c.

Finally, the bar diagrams in Fig. 3d show that there are also slight differences between the three “Terzi” (C), (CM) and (SM). Indeed, by putting the columns together in pairs as in Fig. 4d we can notice that (C) and (CM) present a better trend compared to the (SM) one, which has higher peaks on the lower awareness levels and vice versa. In other words, (SM) seems to be flatter than (C) and (CM), which instead show a bell-like pattern.

This analysis shows that age, gender and education are all important predictors of climate change awareness, consistently with the findings in [26]. We have further found, in our study, that the “Terzo” of residence is another discriminant of attitudes toward climate change. Moreover, the strongest one is the educational level, as also obtained by the authors of [27–33]. Figures 3c and 4c, indeed, highlight a substantial difference between respondents with a middle school diploma (MS) and those with a high school diploma (HS) or a degree (D), indicating that the former are significantly less aware. Figures 3b and 4b show that also gender is a significant predictor of climate change awareness. In particular, our study confirms the phenomenon known as eco-gender gap according to which women tend to have slightly more environmental-friendly attitudes than men and which has been observed in many other researches [34–36]. Regarding the age predictor, it first occurs that the least aware age group is the Over 60 years and this is in agreement with many other studies showing that the older age categories are the least concerned about climate change [57, 58]. Nevertheless, the remarkable result emerging from our analysis is that the youngest age group 14–25, which is also the least

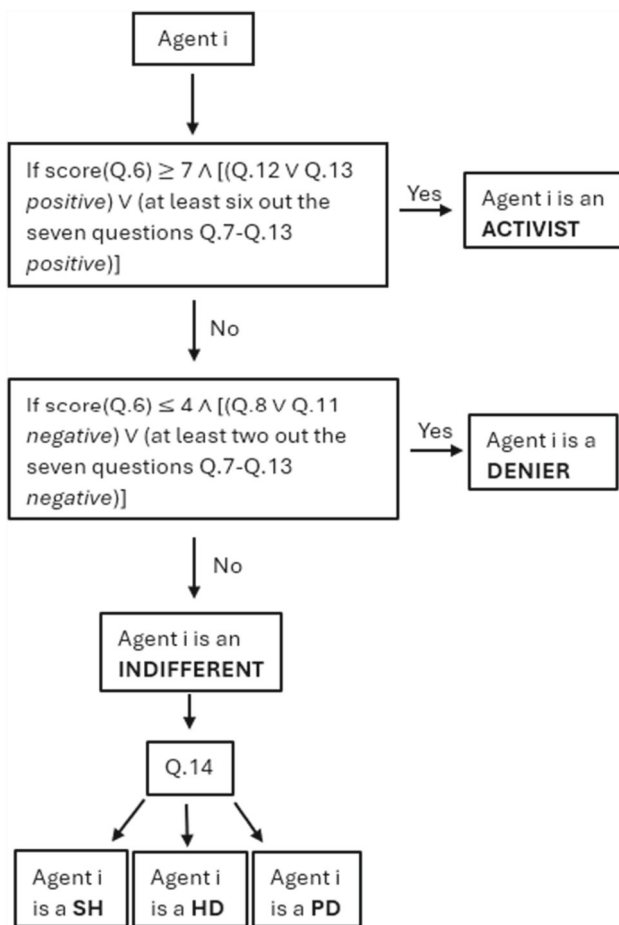


Fig. 5 Agents' classification rule

numerous, is less aware than the 25–40 and 40–60 age classes.

3.1.1 Agents' classification

Concerning the sample composition, from the nine questions in Section B of the survey we can subdivide the respondents into the five types of agents (A), (D), (PD), (SH) and (HD).

All questions Q.7–Q.13 have three qualitative answer options, which are categorized as positive, indifferent and negative, and are used together with question Q.6 to identify whether a respondent is an activist, a denier or an indifferent agent. We use both a qualitative and a quantitative approach to determine the agent type, as shown in the scheme of Fig. 5.

Specifically, the pre-requisite of an agent to be considered activist is that he has a high climate awareness level: $\text{score}(Q.6) \geq 7$. The second necessary condition is that at least one of the two following statements is fulfilled: (i) the agent responds positively to both questions Q.12 and Q.13, (ii) the agent answers positively to six out of the seven questions Q.7–Q.13.

Qualitatively, we have identified questions Q.12 and Q.13 as essential in the determination of an activist,

since cleaning public places or paying attention to environmental impact in purchases are deliberate actions and not dictated by rules or laws as is the case for waste sorting, recycling materials or water and energy consumption.

Quantitatively, the requirement for activists to answer positively to at least six out of the seven questions Q.7–Q.13 reflects the fact that being an activist requires a constant and widespread engagement in multiple aspects of sustainable practices. Moreover, in this way we can ensure that activists answered positively to at least Q.12 or Q.13, which are, in our opinions, essential in determining pro-environmental behavior.

The same reasoning can be made to identify the deniers. The pre-requisite of an agent to be considered denier is that he has a low climate awareness level: $\text{score}(Q.6) \leq 4$. The second necessary condition is that at least one of the two following statements is fulfilled: (i) the agent responds negatively to at least one of questions Q.8 and Q.11 (ii) the agent answers negatively to at least two out of the seven questions Q.7–Q.13.

Analogously to before, we have identified Q.8 and Q.11 as essential in the determination of a denier as they are both related to separate waste sorting, which is a consolidated practice since many years to fight climate change.

Finally, giving a negative answer to at least two of the seven questions Q.7–Q.13 indicates significant resistance to sustainable practices, as these questions cover a range of key sustainability-related behaviors, thus it is associated to deniers.

Respondents who fulfill neither the condition for being activists nor the one for being deniers are classified as indifferent. Among them, an agent is defined as (i) imitator of the majority of neighbors, (ii) imitator of the best neighbor, (iii) opponent of the majority of neighbors, depending on the three corresponding answer options to question Q.14.

The criterion just described has been applied to our sample of 324 agents, giving rise to five classes of agents, each of them is associated to a different game, according to the considerations reported in Sect. 2.3:

1. 33 Activists (A)
2. 15 Deniers (D)
3. 276 Indifferent, subdivided as follows:
 - (a) 45 Indifferent imitators of the majority of neighbors (SH)
 - (b) 34 Indifferent opponents of the majority of neighbors (HD)
 - (c) 197 Indifferent imitators of the best neighbor (PD)

The robustness of the chosen classification criterion has been tested using a twofold approach. Firstly, our results show that the sample of 324 agents contains 10% activists and 4.6% deniers, consistently with the results found in [59,60]. Secondly, by applying small variations to the thresholds used in the selection criteria, such as for example by defining an activist for $\text{score}(Q.6)$

≥ 6 and a denier for $\text{score}(Q.6) \leq 3$, we obtained slight changes in the agent distribution: 22 (A), 12 (D), 47 (SH), 35 (HD) and 208 (PD).

3.2 Model description

The ABM was initially developed in a theoretical case, called the basic model, in which the 324 agents have all the attributes obtained from the survey except for the geographical position on the map of Siena. Thereafter, the ABM was fully adapted to our case study, the so called Siena model, in which the 324 agents are georeferenced on the map of the city.

3.2.1 Basic model: equidistributed agents

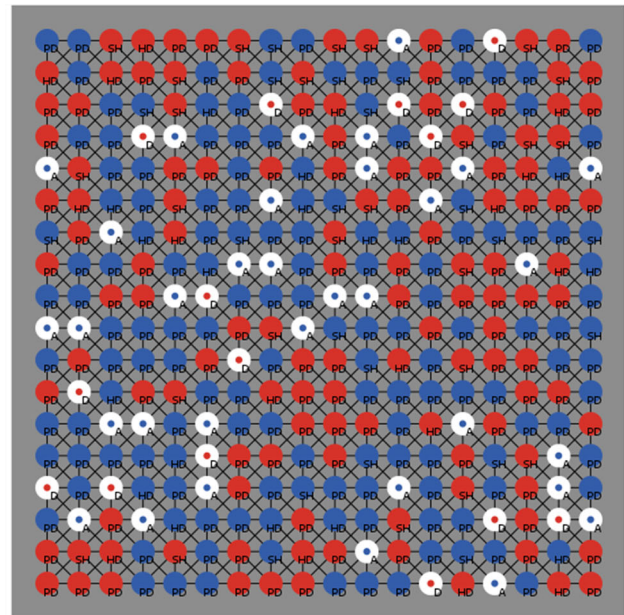
The basic model simulates the behavior over sustainable practices of single individuals living in a city with a prototypical regular structure. The ABM contains a total number of $N = 324$ agents positioned to form a two-dimensional lattice and who make decisions on issues having an environmental impact, from waste sorting to energy and water consumption. The agents in the model do not move and thus they are identified with their home location. Moreover, agents interact with each other and these interactions are represented by the links of a graph on which the ABM is located, in such a way that the DM process depends on both such interactions and GT.

The purpose of the model is to understand under what conditions there is diffusion of sustainable practices among citizens, and then, in terms of GT, to analyze the dynamic and emergence of pro-environmental cooperative behaviors.

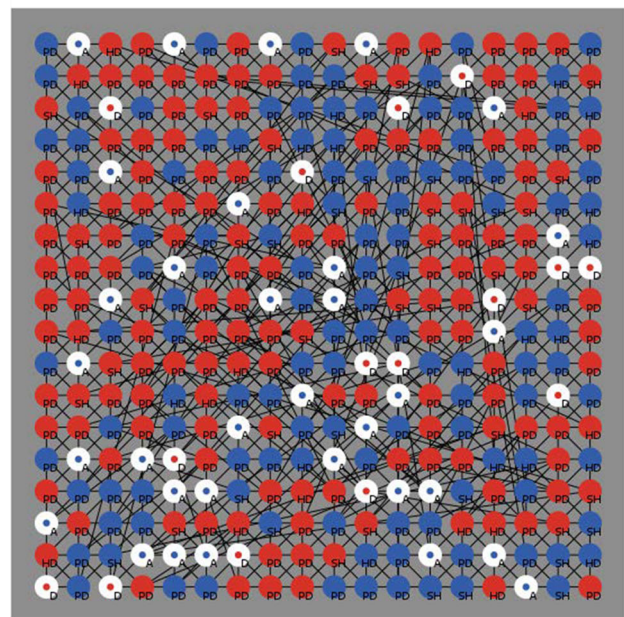
The 324 agents of the model are classified into the five types described in Table 5 following the criterion stated in Sect. 3.1.1: 33 (A), 15 (D), 197 (PD), 45 (SH) and 34 (HD). Therefore, each agent belongs to one and only one of these five classes and never changes it. The five agent types are displayed in Netlogo using labels with the same acronyms (A), (D), (PD), (SH) and (HD) (see Fig. 6).

Agents belonging to the three indifferent types (PD), (SH) and (HD) can change strategy (cooperation or defection) at each iteration of the model. The strategy selection by each (PD), (SH) and (HD) player is described using colors [47], as shown in Table 6. Specifically, an agent has color: (i) blue, if he cooperates in both the current and previous round; (ii) red, if he defects in both the current and previous round; (iii) green, if he defects in the current round and cooperated in the previous one; (iv) yellow, if he cooperates in the current round and defected in the previous one.

Activists (A) and deniers (D), on the other hand, always choose the same strategy and are therefore represented in the model as white nodes with: (i) a blue central dot in the former case, because the fixed strategy is cooperation; (ii) a red central dot in the latter case, because the fixed strategy is defection (see Fig. 6).



(a)



(b)

Fig. 6 The two different graphs for the basic model depicted at time $t = 0$ and with $ic = 50\%$. In **a** we have the regular lattice with $SWrp = 0$, in **b** the small-world network with $SWrp = 0.05$. The type of each agent is represented by a label A, D, PD, SH or HD. Each agent of type (PD), (SH) and (HD) is initialized either as a cooperater (blue node) or as a defector (red node). Activists (A) and deniers (D) are represented by white nodes with a blue and red central dot, respectively

Table 6 Color coordination to strategy; C = cooperate and D = defect

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

According to the survey schema, each agent in the model has the discrete variables $age \in \{14-25, 25-40, 40-60, \text{Over}60\}$, $gender \in \{F, M\}$, $educational\ level \in \{MS, HS, D\}$, $awareness \in [1, 10]$ and $kind \in \{(A), (D), (PD), (SH), (HD)\}$. The values of these variables are randomly assigned in the initial phase (at $t = 0$) to each agent so that the percentages of each age, gender, educational level, and kind category found by the survey are fulfilled and in such a way that the assignment of the awareness variable follows the criterion for the sample composition expressed in Sect. 3.1.1. Each agent also has associated the continuous variable $score$, which is assumed initially equal to 0 and free to change over time. In particular, let i be the i th indifferent agent and let $total-cooperators (tc)$ denote the total number of cooperating agents connected to agent i via the graph of the ABM. Then its $score$ is updated according to the following rule [47]:

$$score(i) = \begin{cases} tc & \text{if the agent } i \text{ cooperate} \\ \alpha \times tc & \text{if the agent } i \text{ defect} \end{cases} \quad (1)$$

where α is the *defection award* parameter introduced in Sect. 2.2.

Besides α , in the model there are two other parameters: *initial cooperation (ic)* and *SW-rewiring-prob (SWrp)*.

The parameter $ic \in [0\%, 100\%]$ establishes the fractions of cooperating and defecting agents at the initial time $t = 0$. More precisely, each indifferent (PD), (SH) and (HD) agent either cooperates (blue color) or defects (red color) at the starting stage of the model and the larger the value of ic , the more cooperators there are at time $t = 0$. Moreover, the initial position of the agents cooperating and defecting is assigned randomly.

The parameter $SWrp \in [0, 1]$ represents the rewiring probability, it is used to build the graph on which the model is located and remains unchanged throughout the entire execution of the model. Concerning the graph we consider two different scenarios: in the first one we have a two-dimensional 18×18 regular lattice where each agent is connected to its eight neighbors except those on the edges which have fewer connections and it is obtained with $SWrp = 0$ (see Fig. 6a); in the second scenario, on the other hand, we have a small-world (SW) graph built starting from the regular one using a rewiring algorithm inspired by Watts and Strogatz's model [61] and got with $SWrp = 0.05$ (see Fig. 6b). The choice of this value for the rewiring probability follows firstly from the fact that the optimal range for $SWrp$

to produce an SW network is $[0.01, 0.1]$, as reported by the authors of [62]. Furthermore, from the simulations, it is obtained that with a number of players equal to 324 the minimum value of $SWrp$ for which changes are observed compared to the regular lattice case is given by 0.05 and that for $SWrp \in [0.05, 0.1]$ no more significant differences are observed.

Since the agents in the model match with their home location, the regular lattice represents a perfectly regular city or neighborhood where only geographical proximity connections are considered in the DM process. Moreover, SW networks are recognized in the literature as the most suitable for representing social phenomena [62, 63], so in the second scenario, the consideration of such a graph allows us to assess the agents' social network of friendships.

For both graphs, we evaluated the ω coefficient, which quantifies the small-worldness properties of the considered network more accurately than the small coefficient σ , which instead compares the clustering and characteristic path length of the network with those of an equivalent random graph [63]. A SW graph is defined by high clustering, like regular lattices, and small characteristic path length, like random graphs [62]. Therefore, ω is computed by comparing the clustering and characteristic path length of the network with those of an equivalent lattice and an equivalent random graph, respectively. The parameter ω takes values in the range $[-1, 1]$ and indicates the transition from regular lattices to random graphs, with intermediate values characterizing SW networks. Negative values of ω suggest that the features of the graph are more similar to those of a regular lattice, with -1 indicating a perfect one. Conversely, positive values indicate that the characteristics are more like a random graph, with 1 denoting a perfect one. When ω approaches 0, it suggests a SW network structure, with 0 revealing a perfect one. The ω coefficients for our two graphs have values approximately equal to -0.63 and -0.21 , respectively, confirming that the former has a more regular lattice structure, while the latter has characteristics very close to a SW network.

Once the model has been set to its initial state, it is ready for execution. Regarding the time horizon, no limits are set, and the unit of time in the model is the Netlogo one: the tick, which in our case represents 1 day.

At each iteration of the model, all players make their decision based on the interactions with others and the game in which they participate. Specifically, the strategy selection mechanism is described by the following outline:

- (PD) players select the same strategy as the agent with maximum score 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.

- (A) players choose always to cooperate independently of the neighbors' decisions.
- (D) players choose always to defect independently of the neighbors' decisions.

3.2.2 Siena model: geo-referenced agents

The ABM has been then fully adapted to the data collected from the survey, thus obtaining the Siena model. The purpose, model entities, and many of the aspects described in the basic model remain essentially the same. Therefore, we simply outline in this section what are the main changes.

The 324 agents, in this case, are also geo-referenced on the map of the city of Siena, which we import into our ABM using the Netlogo GIS extension [64, 65]. In detail, we start by importing the map of the entire Italian road network, obtained from [66], then, by setting minimum and maximum values for latitude and longitude, a zoom of the map is made on the square to include the historical center of Siena (see Fig. 7).

For the sake of geo-referencing, each player, in addition to the variables described in the basic model, has also the following ones: *terzo*, *location*, *lat* and *long*. The variable *terzo* indicates the neighborhood of the city of Siena (C), (CM) or (SM) where the selected agent lives. The variable *location* reports the address (without house number) of residence of the considered agent. Finally, the variables *lat* and *long* specify latitude and longitude of the agents, respectively. With these additional features, we can move each agent to its actual geographic location on the previously imported map of Siena (see Fig. 8).

The main difference with the basic model is that in the Siena model each agent's variable is assigned its own value obtained from the survey, including geo-reference, and imported into Netlogo. Therefore, the only randomness element remaining in the Siena model is the initial distribution of cooperating (blue nodes) and defecting (red nodes) indifferent agents, since activists and deniers have fixed cooperative and defecting behaviors, respectively.

Also in this case, two scenarios are investigated with regard to the graph. In the former, we have a geographical network, obtained with $SWrp = 0$, whose links represent Siena's neighborhood connections and in which each agent is linked to all those within a radius 10 from itself (see Fig. 8a). This radius is evaluated in terms of patches present in the Netlogo world, and 10 is the minimum distance for having a connected graph. It corresponds to about 120 ms. In the latter scenario, instead, a SW network is built from the geographical one using the same rewiring algorithm as in the basic model with $SWrp = 0.05$ (see Fig. 8b).

Similarly to the analysis performed for the basic model, we have evaluated the small-worldness of the rewired graph. The ω coefficients for the two networks for the Siena model take values approximately equal to -0.61 and -0.19 , respectively, confirming that the geographic graph has a structure similar to a regular



(a)



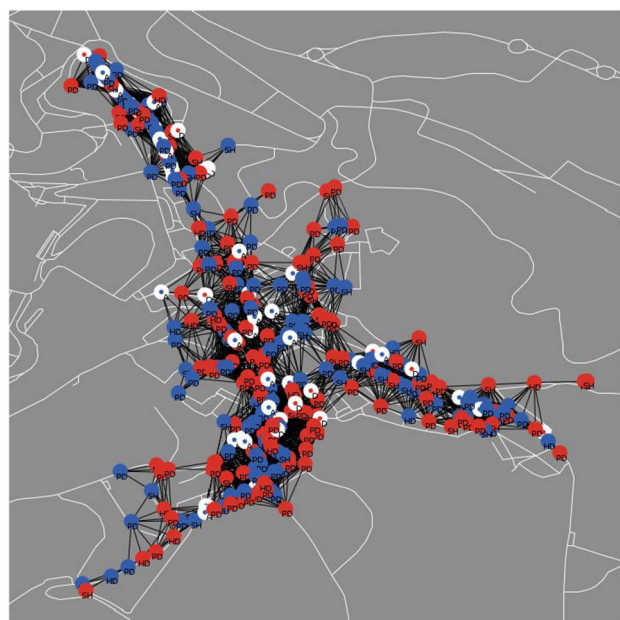
(b)

Fig. 7 Maps in the Netlogo world display: **a** the entire Italian road network, **b** the historic center of Siena

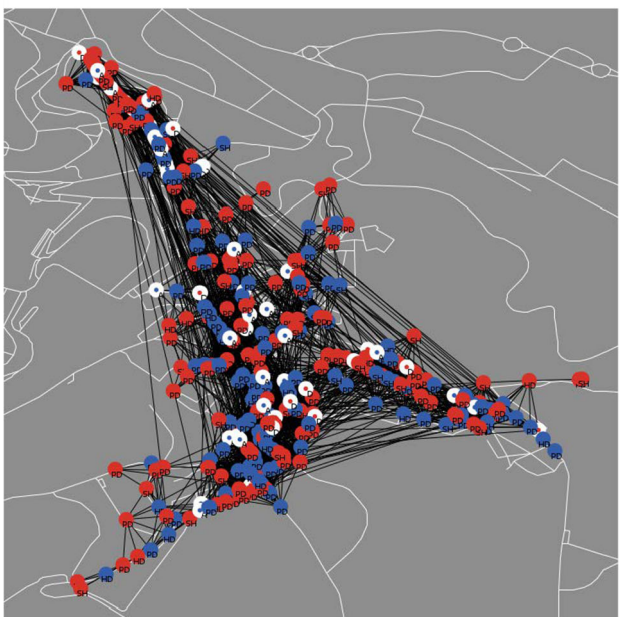
network, while the second one has characteristics very close to a SW network. Thereby we analyze in the DM process, as in the basic model, for the first scenario only the neighborhood connections, and for the second one also the social network of citizens' friendships.

3.2.3 Basic and Siena model parameters and variables

This section summarizes the main model parameters and variables, distinguishing between those obtained



(a)



(b)

Fig. 8 The two different graphs for the Siena model depicted at time $t = 0$ with $ic = 50\%$. The white lines represent Siena's road network, while the black ones are the links between nodes. In **a** the graph is the geographic one, got with $SWrp = 0$, in **b** the graph is the SW one, got with $SWrp = 0.05$

from the literature and those adapted from the survey, as shown in Table 7.

The model parameters α , ic and $SWrp$, whose meaning is explained in Sect. 3.2.1, have been obtained from the literature.

Table 7 Parameters, state and global variables of the basic and Siena model, and their reference to literature and our survey

Model parameters	References
α (defection award)	Ref. [47]
ic (initial cooperation)	Ref. [47]
$SWrp$ (rewiring probability)	Refs. [61, 62]
<i>State variables</i>	
Age	Q.1
Gender	Q.2
Educational level	Q.3
Awareness	Q.6
Kind	Q.7–Q.14
Score	Ref. [47]
Terzo (Siena model)	Q.4
Location (Siena model)	Q.5
Lat (Siena model)	Q.5
Long (Siena model)	Q.5
<i>Global variables</i>	
Total-number-of-agents	Q.1–Q.14
n-of-activists	Q.7–Q.13
n-of-deniers	Q.7–Q.13
n-of-indifferents-SH	Q.14
n-of-indifferents-HD	Q.14
n-of-indifferents-PD	Q.14

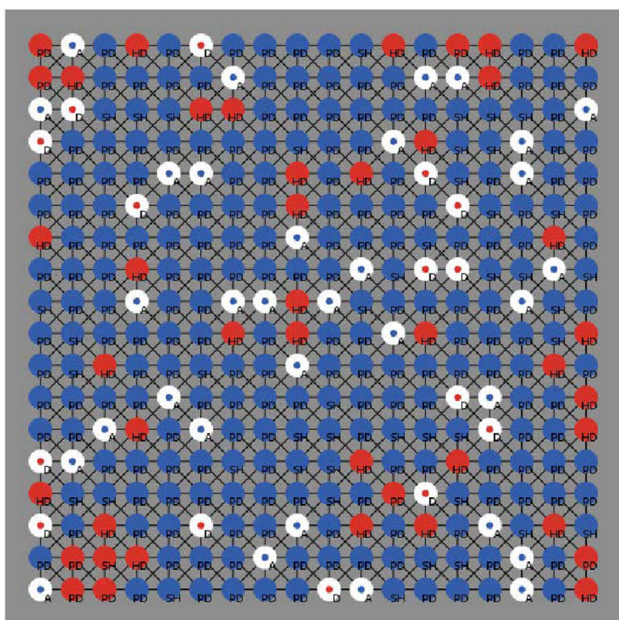
The variables in the model are divided into state and global variables. The former are the agent's own variables, while the latter are the general variables of the model. In the first class, there are the variables *age*, *gender*, *educational level*, *awareness*, *type*, and *score*. They have been all adapted from the survey results, with the exception of the *score*, which varies at each iteration of the model for each agent according to the formula 1 of Sect. 3.2.1 and it is obtained from the literature. Furthermore, in the Siena model there are also the four variables *terzo*, *location*, *lat* and *long*, also obtained from the survey.

The global variable class includes *total-number-of-agents*, *n-of-activists*, *n-of-deniers*, *n-of-indifferents-SH*, *n-of-indifferents-HD* and *n-of-indifferents-PD*. They represent, respectively, the total number of agents (324), activists (33), deniers (15), SH players (45), HD players (34), and PD players (197) and their values were set according to the survey results.

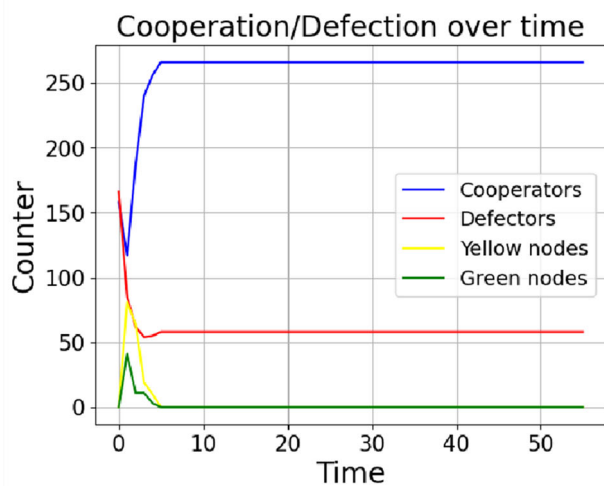
4 Results of the basic and Siena ABM models

This section is devoted to the analysis and comparison of the simulations of our ABM, in both versions: the basic and the Siena model. A multi-run approach is used in all numerical simulations in order to produce robust results.

Basic model simulations are examined in the two scenarios mentioned in Sect. 3.2.1 and shown in Fig. 6: the



(a)



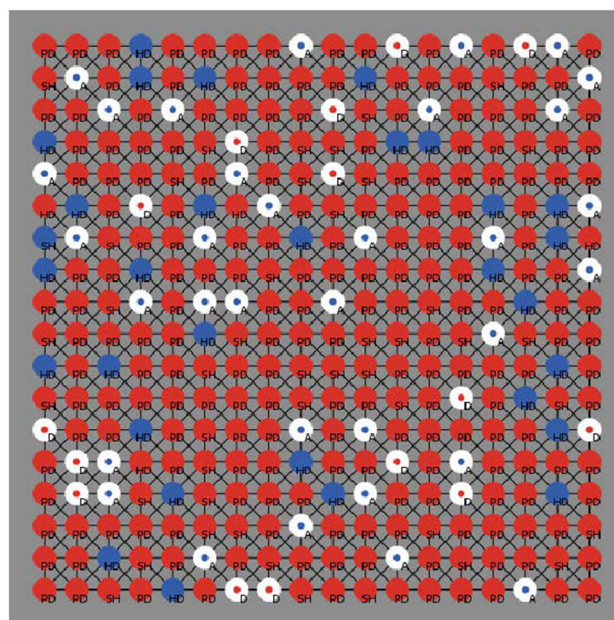
(b)

Fig. 9 Regular lattice scenario. **a** Pattern at final time with $\alpha = 0.8$. **b** Cooperation/defection over time with $\alpha = 0.8$

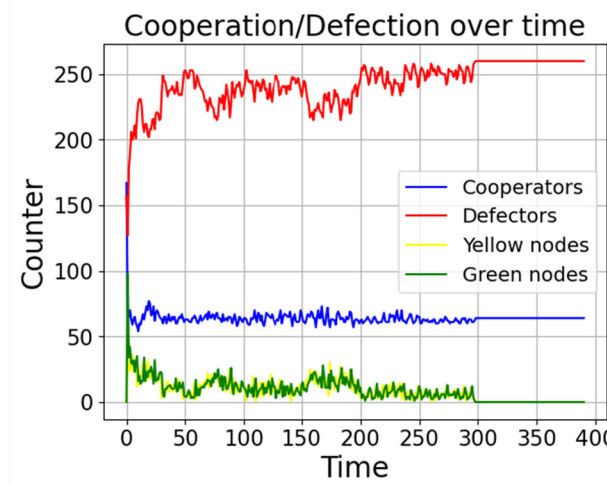
regular lattice and the SW network case. For each of the two graph topologies, we have performed many simulations to study the effect of changing the parameters ic and α . In any case, we find that the dynamic is independent from the value assumed by ic .

For the regular lattice, prevalence of cooperative behavior is observed for $\alpha \in [0, 1.34]$, conversely defection prevails for $\alpha \in (1.34, 3]$, as shown in Figs. 9 and 10, where the two cases $\alpha = 0.8$ and $\alpha = 1.7$ allow one to observe the differences.

No clusters of cooperation and/or defection are observed in any case, but only global scenarios of sustainability or unsustainability. Furthermore, due to the



(a)



(b)

Fig. 10 Regular lattice scenario. **a** Pattern at final time with $\alpha = 1.7$. **b** Cooperation/defection over time with $\alpha = 1.7$

features of our specific sample of agents, the dominant component is represented by (PD) players, who are the only ones whose decisions depend on α . For $\alpha \in [0, 1.34]$ (PD) players predominantly cooperate. Consequently, (SH) players mostly cooperate too, while (HD) ones mainly defect, being imitators and opponents of the majority of neighbors, respectively. For the same reasons, when $\alpha \in (1.34, 3]$ (PD) players predominantly defect and accordingly (SH) players too, while (HD) ones mainly cooperate.

For the SW network, the overall dynamic remains almost the same. The key difference that is observed lies in the threshold for α at which there is a behavioral

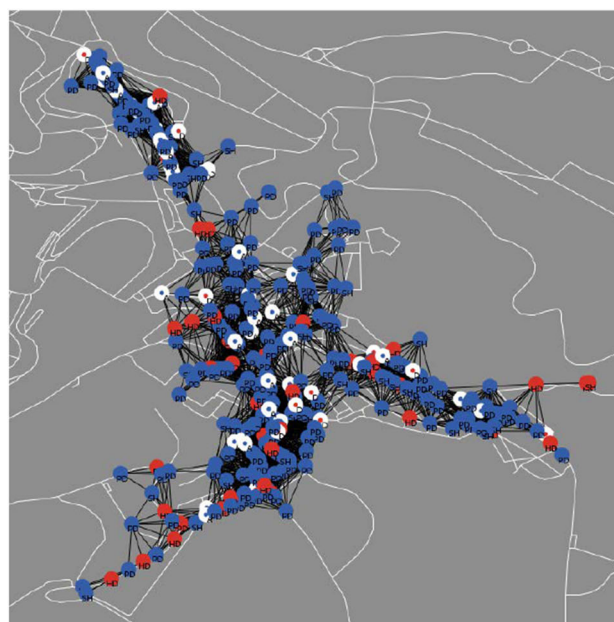
change from the cooperative to the defecting dynamics. We find prevalence of cooperation for $\alpha \in [0, 1.38]$ and defection for $\alpha \in (1.38, 3]$, enabling us to conclude that the SW network is slightly more cooperative than the regular one.

Siena model simulations are analyzed in both the scenarios introduced in Sect. 3.2.2 and shown in Fig. 8: the geographical and the SW network. The dynamic is again independent of the value assumed by ic in any case and depends only on α . As in the basic model, either with the geographical or SW network, by increasing the value of α from 0 to 3, (PD) players shift from cooperation to defection. Consequently, (SH) players show the same dynamics, while (HD) ones move from defection to cooperation. Specifically, for the geographical network scenario we observe prevalence of cooperation if $\alpha \in [0, 1]$ and defection if $\alpha \in (1, 3]$, while for the SW network scenario we get the prevalence of cooperation if $\alpha \in [0, 1.12]$ and defection if $\alpha \in (1.12, 3]$. Figures 11 and 12 show two examples with $\alpha = 0.8$ and $\alpha = 1.7$ proving the differences in the former scenario.

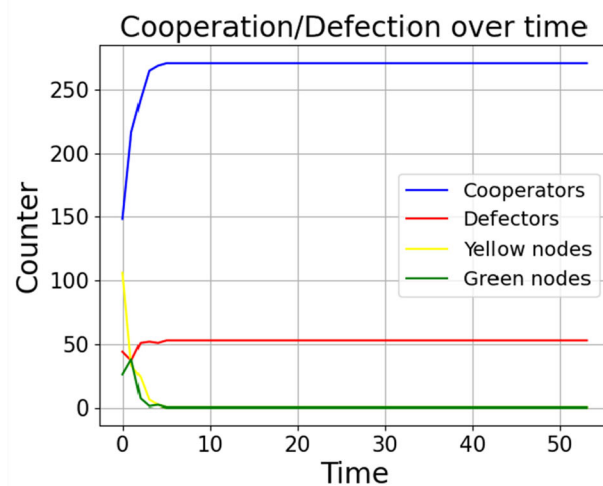
Similarly to the basic model we find that the SW network is slightly more cooperative than the geographical one.

Summarizing, we get prevalence of cooperation for $\alpha \in [0, \alpha_1]$ and defection for $\alpha \in (\alpha_1, 3]$, where the value of α_1 depends on the model and on the considered scenario. Comparing for both models the scenario which takes into account only neighborhood connections (regular lattice in the basic model and geographical network in the Siena model) with the one evaluating also the social network of citizens' friendships (SW networks) it is evident that the presence of a SW network slightly promotes the spread of cooperative behavior, according also to the results found by the authors of [67], where it has been analyzed how cooperation emerges in the spatial prisoner's dilemma played in a range of networks, from regular to random, and where it has been proved that the SW topology is the optimal one for the spread of cooperation. Analogously, in our study for both the basic and Siena models, the α range where cooperative behavior is prevalent increases when moving to a SW network.

In Table 8, we report the values of α_1 calculated in all cases to highlight the differences between a perfectly regular city and the real geographical network of Siena. The threshold $\alpha_1 = 1$ obtained in the latter case is significantly smaller than the one obtained in the former, $\alpha_1 = 1.34$. This means that the range of α where there is prevalence of cooperation is much smaller in the case of Siena. The same observation can be derived when comparing the two SW network scenarios. In fact, the threshold $\alpha_1 = 1.12$ obtained in the Siena model is again significantly lower than the threshold $\alpha_1 = 1.38$ achieved in the basic model. These results imply that the diffusion of cooperative behavior is more difficult in the medieval city of Siena than in a perfectly regular one, thus opening interesting questions regarding the impact of urban structure on policies aimed at fostering sustainable behaviors of citizens.



(a)



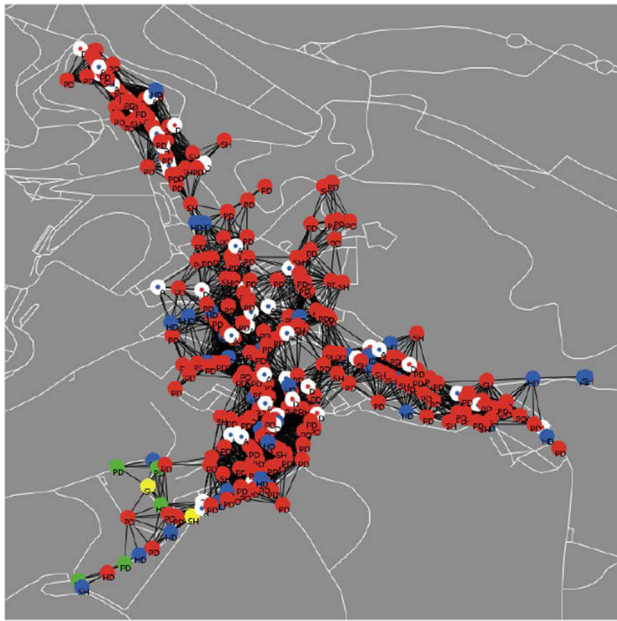
(b)

Fig. 11 Geographical network scenario. **a** Pattern at final time with $\alpha = 0.8$. **b** Cooperation/defection over time with $\alpha = 0.8$

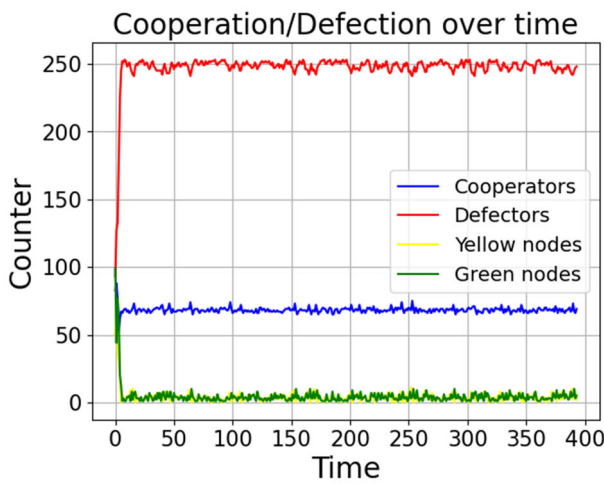
4.1 Sensitivity analysis

To understand better the model results we have performed the sensitivity analysis on the parameter α_1 . For an easier interpretation of the results, we have restricted the study to the basic model in the regular lattice scenario, where we found $\alpha_1 = 1.34$.

In Table 9 we report the results of the simulation experiments we developed to evaluate the sensitivity of the parameter α_1 . Starting from the subdivision of the sample obtained from the classification rule explained in Sect. 3.1.1, we varied the number of agents of pairs



(a)



(b)

Fig. 12 Geographical network scenario. **a** Pattern at final time with $\alpha = 1.7$. **b** Cooperation/defection over time with $\alpha = 1.7$

of groups by exchanging different shares of individuals among them.

Table 8 Thresholds for α indicating the transition from cooperation to defection in the basic and Siena model across regular (R), geographical (G), and small-world (SW) network scenarios

Basic model	Siena model
(R) $\alpha_1 = 1.34$	(G) $\alpha_1 = 1$
(SW) $\alpha_1 = 1.38$	(SW) $\alpha_1 = 1.12$

Table 9 Sensitivity analysis for the parameter α_1

	A	PD	SH	HD	D
A		1.31 1.31 1.32	1.32 1.35 1.35	1.29 1.28 1.24	1.3 1.26 1.19
PD	1.33 1.33 coop. $\forall \alpha$		1.35 1.35 1.61	1.3 1.25 0.97	1.21 1.22 0.52
SH	1.32 1.28 1.26	1.3 1.28 1.26		1.28 1.24 1.17	1.29 1.23 1.15
HD	1.33 1.33 1.37	1.33 1.35 1.39	1.33 1.35 1.37		1.3 1.32 1.31
D	1.33 1.33 1.36	1.33 1.33 1.35	1.32 1.3 1.31	1.3 1.32 1.32	

Specifically, the three colors red, black and blue of the α_1 values given in a cell (i, j) correspond to a 10%, 30% and 50% decrease in the population of row i , and a simultaneous increase in the population of column j , respectively. The results in the Table show that small variations in the proportions of player types do not cause large changes in the value α_1 . Conversely, the larger are the variations in the proportions of player types in the model, the more significant are the changes in α_1 , and thus in the system's cooperation propensity. In particular, we notice the presence of the recurrent mechanisms:

- Increasing the number of (HD) players causes a decrease of α_1 .
- Increasing the number of (SH) players causes an increase of α_1 .
- Increasing the number of (A) players causes an increase of α_1 .
- Increasing the number of (D) players causes a decrease of α_1 .

On the other hand, for the (PD) players the cooperation level depends on the type of players they switch with. For example, higher cooperation levels are observed by exchanging (PD) with (A) or (SH) players, while lower cooperation is obtained by substituting (PD) with (D) or (HD) players.

5 Discussion

The study presented in this paper has allowed us to investigate climate awareness and attitudes toward environmental sustainability using a representative sample of 324 agents of the historical center of the art city of Siena, whose residents on 31 December 2023

are 10352 [68]. The first step in achieving this goal has been the distribution of a survey specifically designed for this research and published for the first time with this paper. A careful statistical analysis of the obtained dataset has permitted us to capture citizens' awareness of climate change. Age, gender, educational level and the district ("Terzo") of residence are all determinants of climate awareness. Educational level is certainly the most significant among them, as it happens in most studies on attitudes about climate change [27–33]. Our data have also confirmed the phenomenon known as eco-gender gap, according to which women are more sensitive toward environmental issues than men [34–36]. In addition, our survey highlights the presence of slight differences in climate awareness among the three "Terzi" subdividing the city of Siena, revealing how the "Terzo" (SM) seems to be the least aware.

The most important and unexpected result obtained from the survey concerns the age predictor. Our dataset reveals that the 14–25 class of younger people is significantly less aware than the 25–40 and 40–60 age groups. In general, younger people are more open to adopt new ideas, sensitive to social and environmental issues, and willing to take action to contrast climate change [37].

The phenomenon occurring here could be explained by the gap in climate awareness between big metropolises and small cities, as documented in [27, 69]. Big cities, in general, invest more in projects regarding environmental sustainability and are more often exposed to climate change effects, such as air and water pollution. This may lead to greater awareness and interest in environmental education [70, 71]. Conversely, small cities are less exposed to different sources of pollution, such as traffic, industries, infrastructures, overpopulation, and environmental issues in peripheral districts. Additionally, Siena is a small city of art among the most sustainable in Italy, especially for its conformation and geographical position. Since 2011, the entire province of Siena has been certified Carbon Neutral [13], and on March 7, 2023, the city won the GSTC certification issued by the Global Sustainable Tourism Council, a worldwide organization founded in 2007 with the goal of determining global standards for sustainable tourism [72]. Indeed, the city of Siena is located in a well-preserved area due to the naturalistic value of the Tuscany region, rarely characterized in the past by extreme weather events, although recent floods. Unexpectedly, the results of our survey suggest that the Siena administration could probably invest more in sustainable education, research, and citizen engagement. We claim that even if a small city appears to be naturally sustainable, its citizens need to be aware of the global environmental challenges and of the steps they can take to contribute to overall sustainability. This suggests to policymakers that there is a need to adopt strategies to raise climate awareness among young people, assuming that a higher level will lead them toward more sustainable choices. Such strategies may include, for example, the creation of targeted educational programs in schools and universities, teaching young people the key concepts, causes, and effects of climate change, the organi-

zation of events and activities involving young people directly, or the use of social media to disseminate information engagingly.

The survey administered in this study has also been used as the starting point for the design of our georeferenced ABM, which reflects the subdivision of the city of Siena into the three neighborhoods also used by the city administration and through which citizens' behaviors concerning sustainable practices have been analyzed over time. In particular, the survey enabled us to classify the citizens of the population under study into five different types, depending on their approach toward environmental sustainability, which correspond to five evolutionary games. The analysis of our sample of 324 agents has shown a prevalence of prisoner's dilemma players: 197 (PD), 45 (SH), 34 (HD), 33 (A) and 15 (D).

The developed ABM has made possible a careful analysis of the spread of sustainable behaviors in the city of Siena, using GT for the DM process.

All the results presented in this paper, including the threshold values of the parameter α_1 , the comparison between the various graph topologies, and the results obtained from the sensitivity analysis could not be derived directly from the survey, since the main findings concern future system dynamics. The temporal dimension's presence in sustainability management outlines the importance of developing mathematical models, such as our ABM, which allow us to simulate possible future states of the system and evaluate the corresponding emerging scenarios.

In detail, our research has focused on the dynamic of cooperation and defection between agents, where cooperation is understood as the will of citizens to collaborate for environmental preservation and vice versa for defection. Our ABM was built initially by imagining a perfectly regular city, called the basic model, which has been later extended to our case study, the Siena model. Both versions have been analyzed in two different scenarios corresponding to two urban topologies: the former takes into account in the DM process only the neighbourhood connections, while the latter considers also the social network of friendships of agents using a small world (SW) graph. The dynamic of the basic and Siena models strongly depends on the defection award parameter (α), which is the benefit each agent gets from defection. Our first finding in both models is that the presence of a SW structure fosters the spread of cooperative behaviors [67].

The last and most significant result was obtained by comparing the two models considering mainly the geographical proximity connections. Our results suggest that the urban structure of the city of Siena exhibits much less capacity in the promotion of sustainability than an ideal and perfectly regular network structure. Indeed, the prevalence of cooperation occurs for $\alpha \in [0, 1.34]$ in the regular case, while for $\alpha \in [0, 1]$ in the Siena case. Comparison of SW topologies for the basic and Siena models has yielded similar results. These findings are interesting and unexpected, as they suggest that the effort needed to achieve a spread of

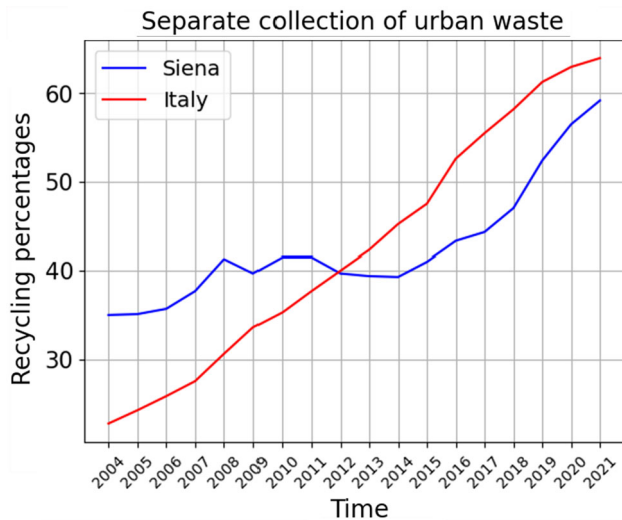


Fig. 13 Time series of recycled urban waste percentages out of the total collected. Data source: Istat—Elaboration on ISPRA data

cooperative behavior among citizens is still high. Therefore, the geographical characteristics of the city on the one hand make it naturally sustainable, but on the other hand, hinder the spread of pro-environmental behaviors.

We have considered the system of indicators for equitable and sustainable well-being (BesT) provided by ISTAT [73], and specifically the time series of one significant indicator for sustainability measurements: the percentage of recycled urban waste out of the total collected (see Fig. 13).

The red line in Fig. 13 shows that urban waste recycling has increased linearly over time in Italy. Conversely, the same indicator for Siena was initially well above average, reversing the pattern from 2012 onward. The blue line shows how the percentage of recycled urban waste remained almost constant for many years, increasing the trend only from 2014 onward, but remaining significantly below the Italian average. This trend is consistent with our findings, revealing how in Siena’s population during recent years climate awareness has been struggling to promote sustainable actions and to be widespread in the population.

Our results have interesting policy implications. The parameter defection award must be kept below the threshold $\alpha = 1$ to have a prevalence of cooperation and consequently to promote sustainable behaviors among citizens living in the historical center of Siena. Keeping α low means promoting a series of policies and actions fostering behaviors that reduce environmental impact and tackle climate change. In the context of environmental policy this could mean, for example:

- introducing economic or tax incentives for the use of renewable energy or low-emission vehicles (necessary in the historical centers of art cities);
- promoting environmental education and awareness programs, information campaigns on the impor-

tance of sustainable actions and the impacts of climate change to increase everyone’s climate awareness;

- supporting research and development of green technologies that provide ecological alternatives to non-sustainable solutions.

5.1 Limitations and future directions

The main limitation of this research concerns the fact that the specific features of each citizen (age, gender, educational level and “Terzo”) as well as climate awareness obtained from the survey, in our ABM are only labels having no effect in the DM process. Among them, we think that climate awareness is the most important as it can have a significant impact on citizens’ decisions, helping or not to promote more sustainable behaviors and choices at an individual level [74, 75]. In this sense, further studies are needed to include in the ABM the climate awareness dynamics in such a way that it also influences agents’ decisions, assuming that a higher awareness can guide toward more sustainable choices.

Moreover, we can take into account different kinds of agents, including tourists, or different kinds of connection structures to consider further relationships among people, such as jobs, occupations, hobbies and free time.

Another possible future direction for this work is the extension of our sample of 324 agents to the real population living in the historical center of Siena (10,352 inhabitants in December 31, 2023) so that simulations can be analyzed on a real scale.

Furthermore, this work can be replicated by taking as case studies other Italian art cities in order to check if also in these cases the urban structure limit the spread of sustainable behaviors.

Finally, the model can be embedded in the context of distributed control. More precisely, the model could include, in addition to the agents mentioned so far, some previously trained special agents, which might be activists or agents with predefined behaviors or even virtual bots capable of interacting with individuals. In this context such special agents can act as nodes of influence in the social network of agents, in particular, they can disseminate information, provide positive examples and guide the agents’ decisions in favor of a common good, which in this case is the environment. The work proposed in our research gives suggestions about what types of agents could be included in future developments of our model with the role of special agents. The sensitivity analysis results of the basic model performed in Sect. 4.1 show that by increasing the number of (SH) players we can raise the α interval where cooperation prevails, thus helping the spread of sustainable behaviors.

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Author contributions

VS, EV and CM developed the mathematical model. VS and EV developed the Netlogo code. VS performed the simulations and wrote the paper. All authors analyzed the results and reviewed the manuscript.

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Data availability The dataset obtained from the survey is available at the following GitHub Repository <https://github.com/vittoriasocci/ABM-for-sustainability.git>.

Code availability The code is available at the following GitHub Repository <https://github.com/vittoriasocci/ABM-for-sustainability.git>.

Declarations

Conflict of interest The authors declare no conflict of interest. The authors declare they have no financial interests.

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