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A review of multilevel modeling and simulation for human mobility and behavior

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ABSTRACT

Multilevel modeling and simulation is a general technique that has many applications in such diverse fields as chemistry, biology, engineering, social sciences and economics. Within these application domains, the study of human mobility and behavior is particularly relevant. Indeed, human mobility is at the basis of important cross-disciplinary research in epidemic modeling, traffic simulation, city planning, and socio-economic studies. Unfortunately, multilevel modeling is mostly used on an "ad hoc" basis due to the lack of consistent terminology and agreed-upon mechanisms. In this paper we perform a systematic literature review of multilevel simulation applied to human mobility and behavior, to identify research trends and contribute towards a better understanding of techniques, methodologies and terminology used within this research area. At the end of our analysis we uncover some recurrent modeling and simulation patterns that appear frequently within specific research areas, and we classify these methodological patterns along several dimensions such as modeling type and level of detail.

1. Introduction

Modeling and simulation is a methodology that consists in reproducing the evolution of real-world entities over time by making use of mathematical or logical models, which describe the behavior of the entities involved and their interactions. This approach can be employed in many scenarios and for various purposes, such as:

- to carry out investigations on highly complex systems, where it would be difficult to analytically study the interactions among the parties involved;
- to evaluate the impact of structural, organizational or environmental changes on a system;
- to investigate the correlation between simulation inputs and the outcome, to understand which are the most important variables and their interactions;
- to study the potential threats to the regular operation of a system (e.g., vulnerabilities, bottlenecks), in order to anticipate issues and deploy improvements ahead of time;

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- to test critical application scenarios, where it is desirable to run tests on digital twins before touching the real system where severe damages to things or people may occur (e.g., medical applications, resilience of buildings to major events such as flooding or emergency evacuations).

A simulated system consists of groups of entities or sets of entities, which are characterized by a set of attributes that denote constant or mutable properties. During the execution of the simulation, certain events may occur, possibly triggered by an action performed by an entity to change the system state.

Multilevel modeling is a methodology that works by representing a system at multiple levels of detail within the same model. This involves some form of decomposition that allows different modeling and simulation paradigms to coexist; the designer is free to choose the modeling paradigm that better fits each level. In this paper, the term “multilevel” does not refer to the mere structuring of a conventional, monolithic simulation into layers (a common software engineering pattern that is frequently used to enforce separation of concerns among sub-components). Instead, we use the term “multilevel” to indicate the use of multiple sub-models within the same simulation. As we will see in Section 2, multilevel models may employ either a hierarchical, flat, or hybrid structure.

Multilevel modeling requires extra effort to ensure consistency among different system representations, but provides significant advantages. First, it allows reuse of existing models, thus reducing time and costs for development and testing. Complex models built upon independent and reusable blocks are faster to develop, test and upgrade, since these activities can be carried out in parallel and bugs might be restricted to a portion of the model. Furthermore, in many scenarios a multilevel approach allows developers to find a good trade-off between accuracy and computational efficiency by restricting the most time-consuming techniques to specific portions while using a more lightweight representation for the rest of the system.

In this paper we review the state of the art in the area of multilevel modeling and simulation; given the broad range of use cases (in chemistry, physics, materials engineering and so forth) we restrict our attention to applications concerning human mobility and behavior. *Human mobility* refers to the study of patterns of individuals’ movement, possibly using different means of transportation, and how those patterns influence, or are influenced by, the environment. Pollution, land use, the diffusion of epidemics, and traffic congestion are examples of issues that are strictly related to human mobility and will be included in the present review. Hence, we use the broad term *human mobility and behavior* as an all-encompassing term for mobility and strictly related issues.

Despite the fact that multilevel modeling is not a novel technique, we found that concepts and terminology are used somewhat inconsistently in the literature. Motivated by the increasing use of multilevel modeling for studying human mobility and behavior (see Section 3), this work attempts to provide a systematic overview by analyzing and classifying the relevant scientific literature.

This paper is organized as follows: in Section 2 we introduce the topic of multilevel modeling by giving some definitions and introducing the terminology that will be used in the rest of this work. In Section 3 we define the methodology that has been adopted to collect and categorize the references; we analyze the data from the quantitative point of view to highlight research trends that help to understand how this research area is evolving. Section 4 through 9 are devoted to the analysis of the scientific literature in the main research areas that we identified; at the beginning of each section we put a diagram that acts as a concept map. Finally, conclusions and general remarks will be provided in Section 10.

2. Multilevel modeling

There are two broad classes of models: *deterministic*, if their evolution is entirely predictable from the initial conditions, or *stochastic*, if their evolution depends on random choices. As far as simulation models are concerned, several paradigms are available, among which the most important are:

Discrete-Event Simulation (DES) where state changes occur at discrete points in simulated time [1]. Discrete simulators can either follow a *time-stepped* approach, where each time-step represents a certain fixed unit of time, or an *event-driven* approach, where timestamped events are executed in chronological order, so that the simulated time between two consecutive steps may vary. DES allows for a compact representation of the system, avoiding the problem of state explosion, which occurs when the possible number of states is huge, making the system difficult to manage and to model check [2] (a system with n process, each having m states, will produce n^m potential states).

Agent-Based Model (ABM) where the system is modeled as a collection of autonomous and interacting entities, each one characterized by specific features and behaviors. The interconnection of the agents with the simulated environment is often of great importance, so that the expression *situated agents* is commonly used to refer to agents that interact with objects of the environment in order to meet their design objectives [3]. Situated agents establish a local relationship with the environment, and their behavior would not make sense outside of it. In other models, agents do not have a strong connection with the environment, since the notion of space is not necessarily relevant for the purpose of the simulation. In these scenarios, the behavior of the agents is defined by the interactions with the other system entities, including other agents. Examples are studies of peer-to-peer systems, as the core of the simulation is the interplay among the various peers. For instance, in [4] an ABM allows for testing the feasibility of cyberattacks on proof-of-work blockchains.

Cellular Automata (CA) where agents are located in a lattice of cells, and update their state depending on the current state of some neighbors [5]. CA may have continuous or discrete state space, and may evolve in continuous or discrete time. CA are often used to carry out investigations on complex systems where the primary focus is the interaction among the agents.

Continuous Simulation where the behavior of components and their interactions is described by a set of differential equations, so that the system state is continuously subject to change [6]. Continuous models enable a more precise simulation of timings, since events can occur whenever appropriate, and also simplify ensuring time consistency with other models if present. System Dynamics (SD) is an incarnation of continuous simulation that uses sets of differential equations to describe the relations among entities, and feedback loops to update the state variables over time [7]. A famous application of SD is the World3 model [8], where five sub-models (population, food production, industrialization, pollution, and consumption of nonrenewable natural resources) are coupled to describe interactions between the Earth and human population, from which the authors argue against the possibility of unlimited economic growth. Note that there are continuous models that are not based on SD, e.g., macroscopic traffic simulators (see Section 5), hence continuous simulation is a proper superset of SD.

Monte-Carlo Methods where the probability of getting certain outcomes is computed by iterating simulations where stochastic decisions are taken for any variable that has inherent uncertainty [9].

Multilevel modeling can benefit from the Parallel and Distributed Simulation (PADS) paradigm, which is an implementation technique where a simulation is run concurrently on multiple execution units, possibly on different machines [10]. Often, the goal of PADS is to reduce the wall-clock time or to make use of distributed computational resources, possibly at the cost of increased complexity of the simulator.

Multilevel modeling is an approach to modeling and simulation where the system is handled at multiple levels, so that the simulation usually consists of different models that cooperate and exchange information. Often the terms *multilevel*, *multiscale*, and *multilayer* are used interchangeably; however small semantic nuances were detected in the state of art, so we try to clarify the terminology by providing a specific definition for these terms. In particular we use:

Multilevel to generically indicate a framework where the system is represented with semantically distinct models, each one describing a specific part [11]. Following this approach, it is possible to employ the simulation strategy that is more suitable to the specific scenario, other than allowing for already existing task-specific models to cooperate in a more complex simulation environment. An example is an epidemic model where one component defines human mobility, while another one is in charge of describing the spread of the pathogen within a population. In some papers, these types of models are sometimes referred to as *hybrid*, *nested* or *hierarchical* models. It is worth noticing that often in the literature the term multilevel refers specifically to hierarchical regression models that take information at both individual and aggregate level [12].

Multiscale/Multi-resolution to indicate a framework where the system is represented at different levels of detail [13]. The detail of a model might refer to the time or spatial dimensions (e.g., reducing the time-step to get a more accurate representation of the real system), or to the behavioral dimension (e.g., mimicking most of the micro-behavior of the real system). Multiscale modeling can be useful because it allows the user to find a trade-off between the computational resources required to execute a model and the accuracy of the results. Indeed, using the maximum level of detail might be impractical not only due to the huge execution time required, but also because microscopic models produce a large amount of data from which metrics of interest could be difficult to distill. Sometimes the term *Multi-resolution* is used as a synonym. Thus, a typical approach is to have a macroscopic simulator managing the global execution, with the possibility to entrust the description of local phenomena to microscopic simulators. Typical examples are traffic models, where micro, macro and possibly meso models coexist. *Mesoscale modeling* refers to models that are between the microscopic and macroscopic levels. For example, mesoscopic traffic modeling might involve grouping related vehicles into "platoons" that are handled as if they were a single vehicle. This lies between microscopic models, where each individual vehicle is taken into account, and microscopic models where only flows are important.

Multi-layer to indicate a framework where the actors of the system are represented as a multilayer graph, which is a data structure composed of a set of nodes, edges, and layers, where the interpretation of the layers depends on the implementation of the model [14]. A specific case of multilayer graphs are multiplex graphs, which is a sort of network of networks where the nodes are located in multiple layers and each layer is characterized by different connections [15]. Examples are models that mimic systems linked with human relationships, where each layer represents some type of social connectivity (e.g., friendship, co-working, family).

It is important to remark that we refer to levels/layers from a semantic point of view; simulators that employ a hierarchical structure just as a software engineering design, but implement a single "monolithic" system model, are not included in this review.

3. Review methodology

Fig. 1 shows the main steps of the methodology that has been employed to select, analyze and classify the papers included in this review.

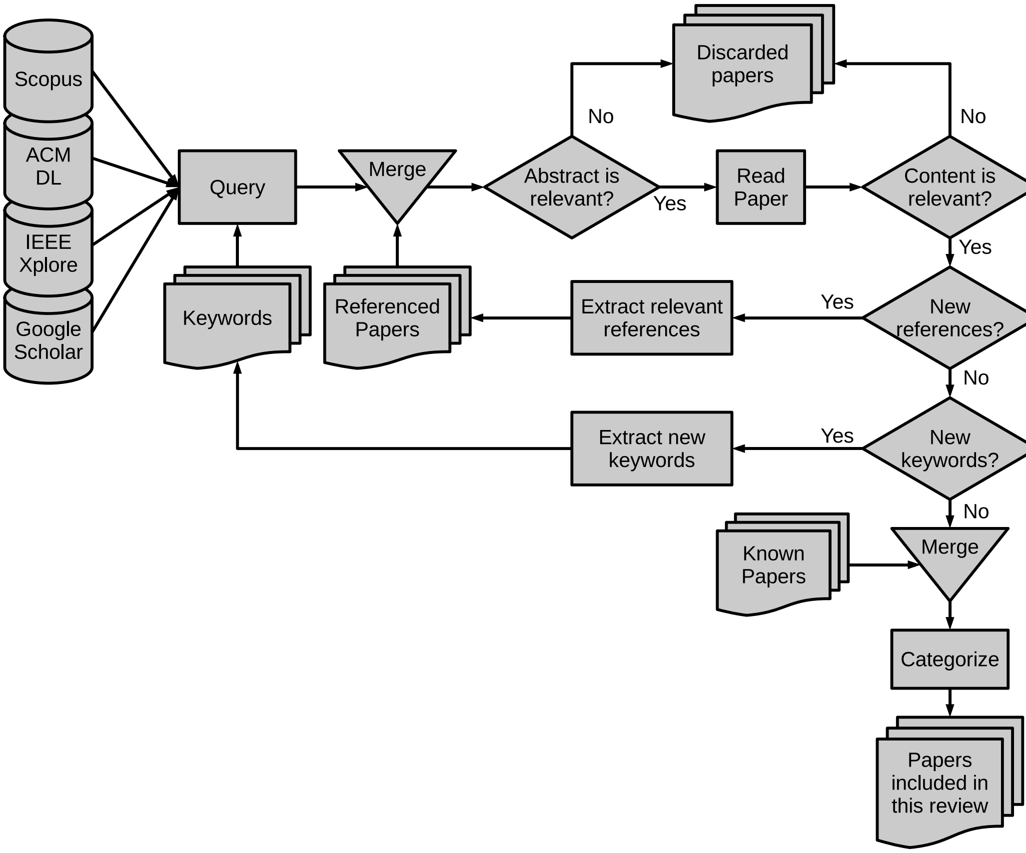


Fig. 1. Steps used to select and classify the papers.

Table 1
Number of matches for each query string on the various bibliographic databases.

Query string	Number of results			
	Scholar	Scopus	ACM DL	IEEEXplore
multilevel modeling	3 000 000	16 752	483 265	12 538
multilevel simulation	1 260 000	3 955	235 720	13 001
multiscale modeling	877 000	16 739	482 544	7 974
multiscale simulation	732 000	3 974	233 658	2 127
multilayer modeling	1 960 000	16 785	482 755	17 341
multilayer simulation	1 760 000	3 993	235 733	7 932

Paper selection. The main sources of the papers are: (i) search engines (Google Scholar, Scopus, ACM Digital Library and IEEEXplore) using a combination of relevant keywords; (ii) references found in the literature above; (iii) personal knowledge, i.e., papers that we are already aware of;

We started with an initial query strings that can be expressed as:

$$(\text{multilevel } \textbf{or} \text{ multilayer } \textbf{or} \text{ multiscale}) \textbf{ and } (\text{modeling } \textbf{or} \text{ simulation}) \tag{1}$$

Since not all bibliographic search engines support Boolean queries, in some cases we had to break the query into several sub-queries by applying the distributive law to (1) to get separate query strings "multilevel modeling", "multilevel simulation", "multilayer modeling", and so on. The list of results of all query strings were then merged by hand.

Each search engine returned a huge number of matches (see Table 1). We instructed each search engine to sort the results by relevance, and selected the first 40 entries for the next phase. We empirically observed that the relevance of results drops quite rapidly so that less than 40 matches, on average, are meaningful for this review.

There is a considerable overlap among the results produced by the search engines. In particular, Google Scholar returned a proper superset of all the matches from IEEEXplore and the ACM Digital Library. Scopus returned a few papers that are not in Google Scholar. Four papers already known to be relevant have been included manually in the pool of papers. Fig. 2 shows the

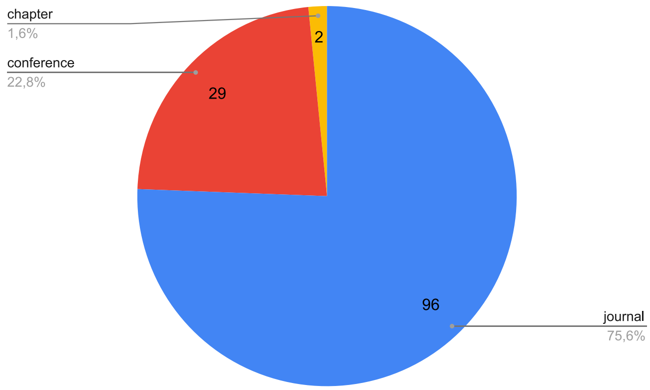


Fig. 2. Fraction of papers by data source.

source of all the papers that passed the filtering step described below. For the sake of graphical simplicity, we attributed to the ACM DL, Scopus and IEEExplore only the papers that did not appear in Google Scholar's search results.

Filtering. To reduce the risk of missing some important papers, the criteria above were quite broad and produced a lot of false positives. Therefore, it was necessary to filter out the results that were outside the scope of this review. To this aim, we first examined the title and abstract, and discarded the papers that are obviously out of scope. This has been proved sufficient to exclude most of the irrelevant papers; some leftovers were removed at a later stage when all remaining publications were read. Papers whose full text was not available or not accessible were excluded; however, the number of unavailable papers was very low, so the completeness of this review was not significantly affected.

Relevant papers were used to identify recurrent application areas so that more narrow searches could be performed, and to extract potentially relevant references that were not included in the results returned by the search engines. Indeed, a significant fraction of papers included in this review come from bibliographic references in other papers (see Fig. 2).

As can be seen from Fig. 1, the paper selection is an iterative process with the "human in the loop", where the initial pool of papers has been enriched through more specific queries and referenced papers. Overall, about 250 papers were examined; about 40% were dropped by looking at the title and abstract, and 10% were excluded after having read the content. The remaining 127 papers are included in this review.

Many papers were discarded because they dealt with topics not related to human mobility; indeed, the terms "multi-level modeling" or "multi-scale modeling" frequently appear in chemistry, physics, materials engineering, and other disciplines in totally unrelated contexts.

Categorization and analysis. After exclusion of unrelated works, the 127 remaining papers were selected to be part of this review. The types of publications are: 96 journal papers (75.59%), 29 conference/workshop papers (23.83%), and 2 book chapters (1.57%). The papers span a temporal range from 1996 to 2022.

All papers have been categorized according to the application area; specifically, the following areas were identified:

- Epidemic modeling (38 papers, 29.92%); discussed in Section 4.
- Traffic modeling, i.e., the study of long-range transportation by vehicles (22 papers, 17.32%); discussed in Section 5.
- Human mobility and crowding, i.e., the study of short-range movements by foot (25 papers, 19.69%); discussed in Section 6.
- Urban Planning and Logistic (17 papers, 13.39%); discussed in Section 7.
- Social Sciences (20 papers, 15.75%); discussed in Section 8.

The application areas above are quite comprehensive, since only five papers (3.94%) did not fit into any of them.

Fig. 3 shows the number of papers by year. To spot possible methodological patterns, we color-coded the histograms according to the fractional counting of geographic areas of the home institution of each author. Fractional counting works as follows: if a paper has n authors, then each one contributes $1/n$ to the count of the geographic area of his/her home institution at the time the paper was written. In case of multiple affiliation, the first one is considered. The Geographic areas are:

- *ASIA*, including China, Japan, Korea, Vietnam, Singapore and so on;
- *EU*, including continental Europe plus the United Kingdom, Ireland, Iceland. Note that we include authors whose institutions belong to national states such as Switzerland and Norway which are not part of the European Union;
- *North America*, including USA and Canada;
- *Other* (rest of the world). Specifically, we included authors from Australia, Brazil, Mexico, Argentina, Nigeria, Senegal, and Morocco.

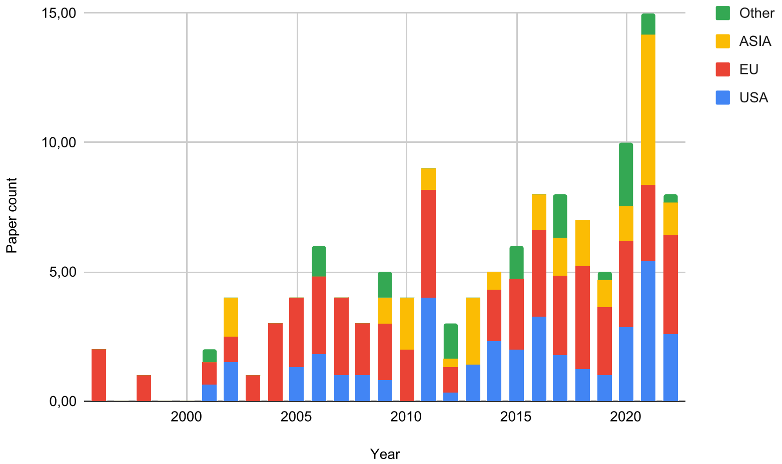


Fig. 3. Paper counts by year and geographic area of the authors.

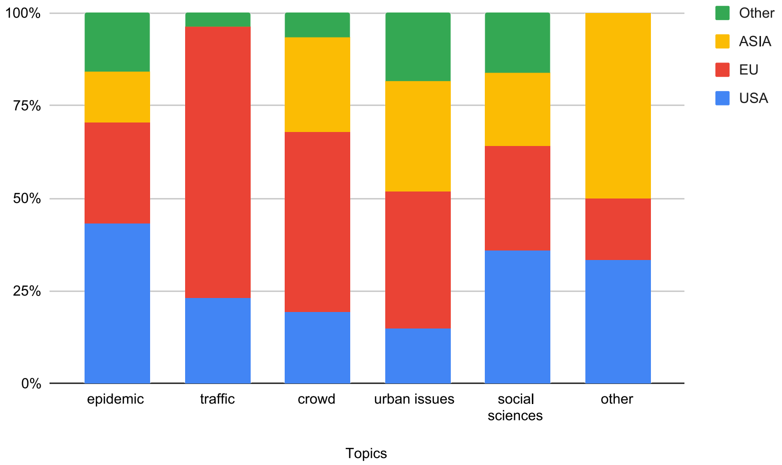


Fig. 4. Contribution to each research topic from authors of different geographic areas.

We can observe that the number of papers dealing with the topic considered in the review grows over time, although it is important to take into consideration the fact that older and newer works are under-represented in electronic libraries. The vast majority of authors worked at an institution in the EU geographic area (56.81 out of 127), followed by USA (36.49), ASIA (22.80) and the rest of the world (10.90).

In recent years we observe a rather steep increase of authors from ASIA. Although one might be tempted that this is due to the COVID-19 pandemic, Fig. 4 shows that this is unlikely to be the reason. Indeed, most of the papers dealing with epidemic spreading come from authors based in the USA and EU; we break down the raw data by year to confirm this fact. Also worth noticing, authors from EU institutions lead (by far) the number of research papers related to traffic simulation through multilevel modeling.

Fig. 5 shows that there is indeed an increasing interest in epidemic modeling in recent years; a clear surge in the number of papers from 2020 onward suggests that the likely cause is the COVID-19 pandemic.

Since reproducibility of research results is becoming increasingly important, we took note of the number of papers where authors provide a reference to the source code of the models or other software artifacts used to produce the results in the paper. For papers using analytical models we looked for machine-readable implementations of the equations used.

Fig. 6 shows that only a few recent publications refer to a public repository where source code is available. While this depicts a rather bleak scenario for the current state of reproducible research in the research topic under consideration, we believe that the situation is slowly improving as many scientific journals are beginning to encourage (or require) authors to provide data and source code whenever possible.

After having defined the field of research, a further classification can be made based on the methodology employed and the scope of the paper, in particular:

- What is the purpose of the paper?

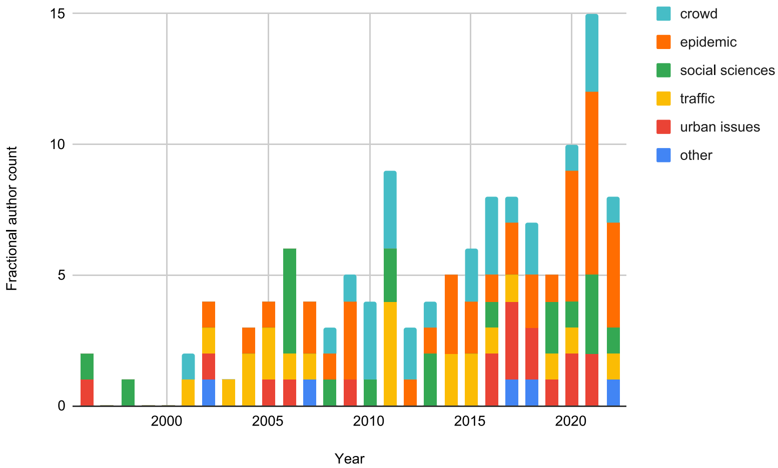
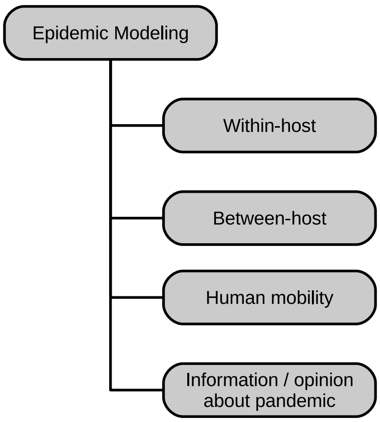


Fig. 5. Breakdown of research topics by year.

- How many levels/scales have been employed? How are they coupled?
- What techniques and simulation paradigms have been used?
- If models are actually evaluated, does the workload consist of real or synthetic data?

4. Epidemic modeling



The unfortunate appearance of COVID-19 at the end of 2019 makes the study on epidemic diffusion particularly topical. The study of epidemic spreading has always been an important research topic; see, e.g., [16,17] and references therein. In general, epidemic models aim at predicting how an outbreak could progress over time, with the goal of studying the effectiveness of containment and eradication policies such as vaccination campaigns or lockdowns.

Since infectious diseases require proximity to, or direct contact with, infected individuals to spread, human mobility plays a fundamental role in the diffusion of epidemics. People can make use of different transportation means (e.g., by foot, car or train, airplane, . . .) that allow a (possibly infected) individual to get in contact with other individuals in the local neighborhood, or within some geographical region, or even in a different country. It is therefore quite natural to employ hierarchical models where each level is in charge of describing interactions at a particular scale (e.g., local, regional, and global).

Several techniques have been developed for multilevel epidemic models. One recurrent framework is the coupling of *within-host* and *between-host* models [18–20]. Within-host models describe pathogen–host interactions, immune system responses and therapies effect [21]; between-host models are concerned with the diffusion pathogens between different individuals, using the results of within-host simulations to determine the transmissibility of the pathogen and the recovery rates [22].

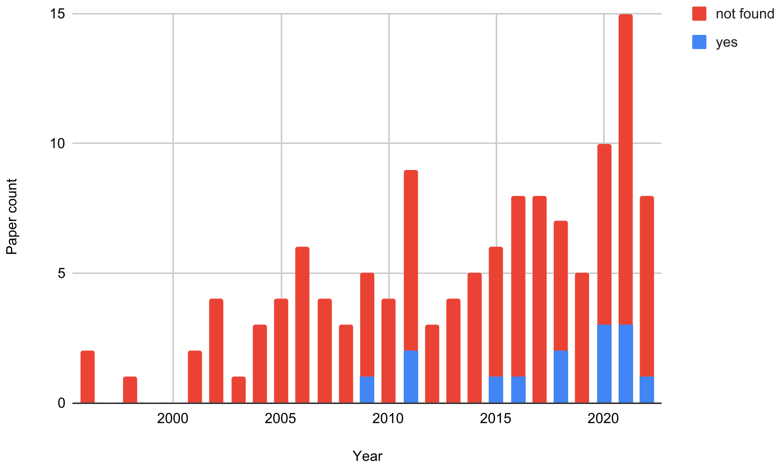


Fig. 6. Number of papers for which source code is available.

Multiple works are based on this methodology to investigate the diffusion of diseases such as Ebola [23,24], Influenza [25], cholera [26], toxoplasmosis [27,28], HIV [29], COVID-19 variants [30,31], as well as non-human diseases like scrapie herd infection [32] or host-parasite coevolution [33].

Usually both within-host and between-host models are based on differential equations. A variety of within-host models exist, but most of them take into account the same features such as number of infected and healthy cells, density of infected and healthy cells, death rate, shedding rate and transmission rate of the pathogen, and so on. Of course, within-host models need to be customized depending on the disease under consideration; for example, in [34] the resistance to antimalarial drugs is also considered.

Between-host models typically rely on a compartmental approach, where the population is split into multiple mutually exclusive categories indicating the epidemiological status of individuals, and suitably defined transition functions describe how agents change the category they belongs to. The use of these models is generally appropriate when one deals with sufficiently large populations, so that it is possible to approximate epidemic trends neglecting transmission dynamics related to specific individuals or groups. At a smaller scale, stochastic transmission events and the characteristics of the population may have a significant influence on the outcome, so that other simulation paradigms such as ABM might be preferable. In general, ABMs are popular in simulation studies regarding infectious diseases [35][36], even though its use in multilevel frameworks is uncommon. The most used scheme for between-host analyses is the Susceptible-Infected-Recovered (SIR) model, where individuals are either *susceptible* (those who are currently healthy but might become infected), *infected* or *recovered* [37]. Transition rates between categories depend on several parameters such as the intrinsic diffusion rate of the pathogen and the mobility pattern of individuals.

Many variants of the SIR model have been proposed where additional states are added to better model the dynamics of infection. One of these variants are the Susceptible-Exposed-Infected-Recovered (SEIR) model, where individuals can also be *exposed* if they have contracted the virus but are still not experiencing symptoms [38], and the Susceptible-Infected-Susceptible (SIS) model, where individuals can be reinfected after recovering from the disease [39]. In [40] the authors proposed to also consider hospitalized people, since hospitalization contributes not only to the care of infected individuals, but also to reduce the spread of the infection. The transmission dynamics is influenced by exposed individuals since they might be silent carriers for most of the contagions. Furthermore, the transmission dynamics is also influenced by the types of interactions among the individuals. For example, in [41] the authors proposed a model where social interactions at home, workplace and public places are characterized by a specific exposure rate, defined as the probability of getting exposed while interacting with silent carriers.

Another multilevel modeling approach – probably the most frequently recurring – consists of coupling between-host compartmental models (usually SIR and SEIR) with models describing individuals' mobility, in order to represent both the spread of the virus within a local area and the diffusion of the pathogens on a global scale. Different models of human mobility exist, but most of them employ some type of graph-based data structure, where nodes and edges represent either individuals and human relationship, or cities and routes. For example, in [42] an air traffic network is built based on real data from USA airports, in [43] a multi-layer network is used, with layers representing different means of transportation and nodes representing either central or peripheral cities, and in [44] the population is placed in a graph, where individuals move to different locations with some probability, and each node is characterized by a specific infection rate, recovery rate, and migration probability. In [45] a purely ABM approach is used, where micro agents represent individuals and meso agents represent groups of hundreds of people. Stochastic decisions are made for managing contagion between infected and susceptible individuals and for moving agents within and between cities. Multilayer graphs are also used for representing human interactions of different nature, like in [46] where multiple layers represent different social connections, such as the social and working environments of individuals [47]. Similarly, in [48] a multilayer network with inter-layer hopping (MNIH) is used, where individuals are the nodes of the graph, layers are different sub-networks and connections occur via both intra-layer and inter-layer edges. Temporal multilayer graphs are instead used in [49] to model the diffusion of sexually transmitted diseases, with two layers representing respectively steady and casual partnerships, while a SIS model is used to model the contagion aspects. Bipartite graphs are used by [50] to represent movements of individuals from their neighborhood to points of interest, based on anonymized mobile phone data.

Human mobility can also be represented through an equations-based approach. In [51] a set of equations is used to describe a population of commuters moving over long distances (extra-urban) and a population of non-commuters acting over short distances (urban). In [52] a molecular-dynamics-based social-force model is employed to model passenger's movements inside an airplane during a flight. In [53] contagions occur stochastically when an infested and a susceptible individual are within the contact radius, while in [54] a social-force model defines agents mobility, with the paper aiming at investigating over the effects of social distancing and mobility restrictions, considering both direct and indirect transmission.

To achieve a realistic representation of inter-cities movements, one may consider the composition of the population to generate more realistic mobility patterns based on socio-economic factors. Following this approach, in [55] the population is represented as a nested hierarchy of sub-populations (i.e., fractions of the overall population characterized by a common feature, such as ethnicity, gender or age). In [56] a mobility model represents the bidirectional recurrent commuting flows that couple two sub-populations, while in [57] both small-scale commuting flow and long-range airline traffic are modeled based on actual airport traffic and connections between sub-populations.

Other solutions for epidemic modeling focus on finding an appropriate trade-off between accuracy and computational effort. For instance, in [58] an adaptive multi-resolution framework is proposed, combining the accuracy of agent-based models with the computational efficiency of equations-based simulations. The model initially starts with the agent-based paradigm, and then switches to an equation-based methodology after a certain threshold of infected individuals is reached, in order to support a population-averaged approach. In [59] a multiscale approach is proposed, where an individual-based model is used for simulating the micro-scale and to provide parameters to the macroscopic SIR model.

Finally, a further possibility for epidemic investigations is to link the diffusion of the pathogen with social factors. In [60] a model describing the awareness of the epidemic is coupled to a SIR model; the authors conclude that awareness of the contagion has a strong impact on the actual diffusion of the disease.

In [61], a multilayer modeling approach is employed for modeling both the epidemic contagion and the spread of opinions regarding social distancing, which of course have an influence on the infection rate. In the information layer individuals are either pro-distancing, anti-distancing or uninformed. Uninformed individuals can be influenced by both opinions depending on their social contacts, so their social neighborhood will affect whether they will follow the rules of social distancing. Similarly, in [62] a graph structure is used to represent a population made of different communities, to describe how dissemination processes of both pathogens and opinions over the epidemic are influenced by interactions between communities. Specifically, opinion dynamics depend on the infected population, the dominant opinion within a community, and the dominant opinions within other communities, while a SIS model represents the local diffusion of the virus.

In [63] both multiple scales and multiple layers are employed. At the macroscale, an agent-based model is used to represent connections between locations to simulate the contagion dynamics. At the microscale, in each node disease transmission and emotional contagion are simulated together with system dynamics mechanisms, using a SEIR model and a newly designed IWAN model (i.e., model where people are either *indifferent*, *worried*, *afraid* or *numb*). Similarly, in [64] the disease and the fear of the disease are modeled in combination, both being described through a compartmental approach; in the model, people can "contract" fear by getting in touch with both infected and scared individuals.

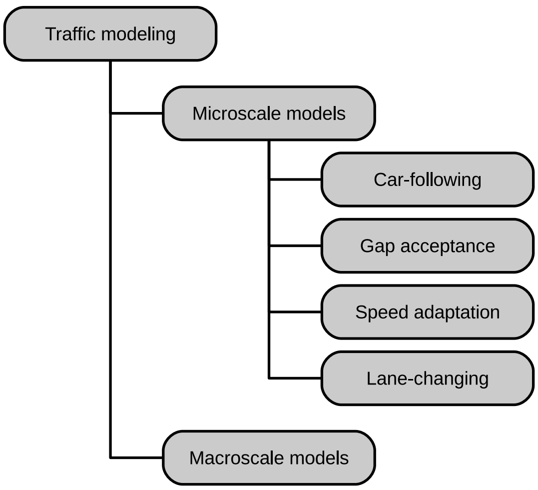
The diffusion of epidemics involves not only the agents that represent affected individuals, but also other external entities such as the public health system, policy makers, and so on. Therefore, it might seem natural to model these external entities as additional layers in a multilevel simulation. However, we could not locate specific research papers using such an approach (see Tables 2–7).

Discussion. Many different approaches are used in the reviewed scientific literature dealing with multilevel epidemic modeling, differing either with respect to the semantic of layers (within-host, between host, metapopulations, social factors, large-scale propagation), or with respect to the modeling paradigm. Compartmental models based on Ordinary Differential Equationss (ODEs) are common, due to their computational efficiency, while ABMs are the preferred choice when more accuracy is required. However, it turns out that taking advantage of ABMs is difficult in practice, because higher accuracy requires more information on the behavior of real-world entities (from the human immune system to whole individuals), and that is rarely available. This is a general rule that applies in every context: the accuracy of a model is at most as good as the knowledge that the developer possesses about the real system. However, ABMs can still be useful even when limited knowledge is available, e.g., to perform "what-if" analyses and infer unknown properties on the real world by trial and error. Unlike traffic modeling (discussed in Section 5) where it is easier to describe micro dynamics in detail, epidemic modeling is often motivated by the identification of trends over time; therefore, population-based models such as SIR and its variants are generally effective. Although pure ABMs are still popular in the epidemiological field, they are mainly used in monolithic simulators.

Table 2
Papers on epidemic modeling (ABM = Agent-Based Model, IWAN = Indifferent-Worried-Afraid-Numb, SEIR = Susceptible-Exposed-Infected-Recovered, SIR = Susceptible-Infected-Recovered, SIS = Susceptible-Infected-Susceptible).

Papers	Methodology
[19,20,22–31,33,34]	within-host + between-host
[32]	within-herd + between-herd
[40]	cellular level + individual level + population level
[42]	SIR + graph for mobility
[43]	SEIR + multilayer graph for mobility
[44]	SIR + mobility graph
[45]	micro ABM + meso ABM
[47]	SIR + multilayer graph
[48]	multilayer network with inter-layer hopping for mobility
[49]	SIS + temporal multilayer graph
[50]	SEIR + bipartite graph for mobility
[51]	SEIR + mobility model
[52]	SEI + force-based model
[53]	pedestrians mobility model + contagion model
[54]	social-force model + PDE-based model
[55]	SIR + hierarchical metapopulation model
[56]	SIR + mobility model
[57]	SEIR + multiscale mobility network
[58]	ABM + equations-based model
[59]	SIR + individual-based model
[60]	SIR + epidemic awareness model
[61]	SIR + continuous-time Markov chain
[62]	SIS + opinion dynamics model
[63]	SEIR + IWAN model + macro mobility ABM
[64]	fear model + contagion model

5. Traffic modeling



Multiscale approaches are frequently used for traffic modeling. In general, microscale models are used to describe the behavior of individual vehicles, macroscale models are used to characterize traffic flows, and mesoscale models are used for modeling individual vehicles through simplified flow dynamics [65].

One of the biggest advantages of multiscale traffic modeling is the possibility to get an appropriate trade-off between accuracy and computational efficiency of the simulation, using micro models to "zoom into" certain critical areas such as places where congestion or incidents happen, and using simpler macro or meso models elsewhere.

5.1. Microscale models

As mentioned, microscale models are employed to describe how individual vehicles behave in response to the environment, which includes road features (signs, traffic lights, number of lanes, and other) and other vehicles in front. This information is used to decide when and where to perform corrective maneuvers such as accelerating, braking, or steering. The state of a vehicle might include the current position and speed, the reaction time of the driver, the maximum speed and acceleration, and so on.

In microscale models, the space over which vehicles move is either represented as a continuum, or using discrete grids, the latter being popular for models based on CA. Also quite common are graph-based representations of road networks, where nodes represent intersections and edges are road segments.

In discrete traffic models the system evolves only at specific points in time; since real traffic evolves quickly, in order not to miss important events the virtual simulation time typically jumps only a few seconds of real time between updates.

Different types of sub-models can be used and combined together for describing the overall behavior of the vehicles at the microscale [66]:

Car-following models where the drivers' behavior depends on the preceding vehicle in the same lane [66].

Gap acceptance models which establish the minimum gap that all drivers are assumed to accept in road intersections: a car coming from a secondary street will get onto the main road if all the vehicles in the main road are more distant than a certain threshold.

Speed adaptation models which adjust the speed of a car depending on the features of the road such as speed limits or quality of road surface;

Lane-changing models which encode the decision to change lane on a multi-lane road link, e.g., to overtake another vehicle or to comply with lane restrictions [67].

Here we list some of the most used frameworks to model traffic at the micro scale:

Intelligent Driver Model (IDM) where a set of ODEs is used to determine the positions and the velocities of single vehicles. Some important parameters for the vehicles are the desired velocity, the safe time headway, the maximum acceleration of the vehicle and the comfortable deceleration [68].

Nagel–Schreckenberg (NaSh) models a cellular automaton where cells can either be empty or occupied by a car. The velocity of the car depends on the vehicle in front and from additional factors [69].

Agent-based models where individual vehicles are modeled as situated agents in the micro environments, and behavioral rules define travel decisions and how vehicles interact with the environment and with other agents [70]. A wide range of (single-level) ABMs is used for the simulation of traffic [71], transportation [72], and autonomous vehicles [73]. Some of the most frequently used simulators in this area are MATSim [74] and SUMO [75]. To deal with a large number of agents, many ABMs use strategies such as *downscaling*, which consists of simulating the entire system's dynamics based on a fraction k of the total population only [76]. Downscaling is often necessary where a huge number of vehicles is involved: with a judicious choice of k, it is possible to cut execution times significantly with minimal loss of accuracy.

5.2. Macroscale models

Macroscale models deal with traffic flow as a whole, so that the behaviors of each individual vehicle is not considered in isolation. Usually, macroscale models use aggregate parameters to describe traffic flows such as *density*, which indicates the number of vehicles per unit road length at any instant of time, *space means speed*, which is the average speed of the vehicles in a certain road section, and *flow*, described as the number of vehicles passing through a point in a certain amount of time. Macroscopic models are usually employed to represent highways or high-speed roads. Some of the most used frameworks to model traffic at the macroscale are:

Network Fundamental Diagram (NFD) which describes the relationship between the number of vehicles in a network and the average flow in that area [77].

Lighthill, Whitham and Richards (LWR) model where the behavior of traffic streams is expressed through the continuity equation and an assumed equilibrium speed-density relationship [78].

Payne–Whitham (PW) model where a set of differential equations describes the traffic by means of mean speed, density and number of vehicles in a certain road segment in a unit of time [79].

Aw–Rascle–Zhang (ARZ) model where a set of second-order, nonlinear hyperbolic Partial Differential Equations (PDEs) describe traffic density and velocity [80].

Table 3
Papers on crowd mobility modeling (ARZ = Aw–Rascle–Zhang, CA = Cellular Automata, IDM = Intelligent Driver Model, LWR = Lighthill, Whitham and Richards, NFD = Network Fundamental Diagram, PDE = Partial Differential Equation, PW = Payne–Whitham).

Paper	Level(s) of detail	Methodology
[65]	micro + meso	AIMSUM simulator
[81]	micro + macro	IDM, PW
[82]	micro + macro	IDM + METANET simulator
[83]	micro + macro	ABM car following model, ARZ
[84]	micro + macro	agent-based models
[87]	micro + macro	multi-agents car following model, PW
[88]	micro + macro	PDE, ABM
[89]	micro + macro	tracking model, ARZ
[90]	micro + meso + macro	Nash, Underwood, LWR
[91]	micro + macro	IDM, LWR
[92]	micro + meso	IDM, mesoscopic LWR
[93]	micro + macro	IDM, LWR
[94]	micro + macro	IDM, NFD
[95]	micro + macro	micro ODE-based model, LWR
[96]	micro + macro	ODE, PDE
[97]	micro + meso	MITSIMLab and MEZZO simulators
[98]	micro + meso	MITSIMLab and MEZZO simulators
[99]	micro + macro	PARAMICS and DYNASMART simulators
[100]	micro + meso	IDM, mesoscopic LWR
[101]	pico + micro + macro	bond graphs, car-following model, macro equations
[102]	pico + micro + meso + macro	equations-based models
[103]	micro + macro	CA, ABM
[104]	micro + macro	agent-based modeling

5.3. Multiscale models

The different scales of the models need to be appropriately coupled, ensuring consistency among the various representations. The most common approach for coupling micro and macro models is aggregation and disaggregation of variables [81–84]. Aggregation means that individual attributes are grouped together, and the result is then treated as a single data point [85]. After aggregation, specific features of individual agents are lost unless some mechanism is used to save and retrieve them. In [86] different aggregation design patterns are proposed for micro agents entering the macro zone. If the information of the micro level is kept, the strategies might differ depending on whether the macro simulator controls the micro agents, or how the different scales are coupled. Disaggregation, on the other hand, enriches and/or splits data points so that features at the macro level can be used to act upon the micro level. Disaggregation might be thought of as creating some new information "from nothing"; therefore, care should be taken to ensure that the new information is nevertheless meaningful. For example, the macro level of a multilevel traffic simulator might be concerned with only the average velocity of vehicles in a particular zone. If disaggregation is used, e.g., to populate a zone with new vehicles in order to focus on some important phenomenon at the micro level, individual velocities should be defined in such a way that their mean is consistent with the macro value, possibly allowing some random variation to reflect what happens in real traffic [87]. In [88] the transition between levels is handled by an entity called "agent upstream". Specifically, the macro–micro transition (called *downstream propagation*) involves the creation of an appropriate number of vehicles from the aggregate traffic flow parameters; the micro–macro transition (called *upstream propagation*) involves the computation of flows and densities from the population of vehicles.

The idea of introduction a transition cell as an interface when switching from macro to micro level is used frequently with the purpose of transmitting limit conditions and to manage the shift from continuous to integer values [89]. In fact, when transitioning from a coarse-grained continuous model to a fine-grained model where vehicles are managed individually, one may experience losses due to the conversion from real to integer values. For example, if the average number of vehicles in a zone is 125.4, then a detailed micro simulation of that zone will create either 125 or 126 vehicles, resulting in a small loss or small gain, respectively. The accumulation of these rounding errors may entail significant variations in the overall number of vehicles. A possible solution is to save and accumulate the fractional part until it reaches a unit, at which point a new vehicle is created [90].

A similar approach is proposed in [91], where "fictitious" vehicles at the end of a scale zone receive the information and transmit it to the other vehicles. In [92,93] the authors propose equations-based solutions for the maintenance of both local consistency (i.e., agreement between models at different scales) and global consistency (i.e., overall preservation of traffic characteristics after several changes of scale). Local inconsistencies may occur when the values of traffic variables are not coherent during the transition between scales, for instance resulting in violation in vehicle conservation, sudden jumps of average speed and unrealistic bottleneck effects. Global inconsistencies may occur when information about traffic composition is lost in the conversion between different scales. For example, vehicles' properties computed in a micro model such as route choices, vehicle features or driving style might get lost in the switch to a macro model, and thus such information would be unusable when switching back to the micro model, unless it was properly stored.

Another possibility for model coupling is illustrated in [94], where the authors propose a service-oriented middleware to allow a macroscopic simulator to work with some microscopic ones. The middleware provides a common interface that can be used by all the parts of the architecture, defining the modes of interaction, orchestrating the execution of the various components and translating data between different scales. In [95,96] a tightly coupled system of partial and ordinary differential equations has been proposed to model, respectively, traffic dynamics and the behavior of specific vehicles, such as autonomous cars or particularly slow and cumbersome vehicles. Other works are not limited to two scales, but also consider mesoscopic and possibly sub-microscopic (also called *picoscopic*) levels. Usually, in mesoscale models vehicles are still considered individually using parameters from the micro model [97,98], and their movements are simulated according to speed-density relationship or based on a macroscopic flow model, as proposed in [99]. Similarly, in [90] the *Underwood* model operates at the mesoscale, differing from NaSh model for the way the vehicles handle their speed, which is dependent on maximum speed, current concentration and capacity of the road, while in [100] the meso model is inspired by the macro NFD model, but with the additional capability of keeping track of single vehicles.

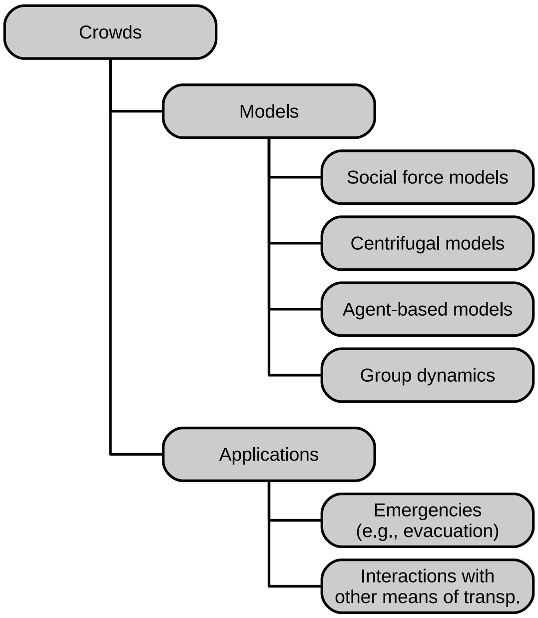
Since vehicles are still treated individually in mesoscale models, no aggregation is required during the switch from a micro model. Thus, model coupling is generally easier, even though some consistency constraints between scales might still needs to be applied. On the other hand, in [101] the sub-microscopic level is represented through a bond graph, in which vehicles dynamics are presented in response to acceleration, braking, steering, considering longitudinal, lateral, yaw, and actuator dynamics of each vehicle. Finally, the authors in [102] propose a framework combining both pico, micro, meso and macroscales. In this scenario, the pico scale consists of a driver and a vehicle model that continuously exchange information in order to determine driving strategies such as braking or steering, while the mesoscale is defined by functions determining the probability of having a vehicle within a certain space and speed range in the unit of time.

An interesting variation of the approaches above has been described in [103], where vehicles are assumed to be equipped with short-range communication technologies that enable data transfer to and from nearby vehicles. Traffic data from the surrounding zone can be collected and aggregated locally within a group of vehicles, and then shared at a higher level among groups. This high-level processing is realized by a number of intelligent agents representing "traffic management centers". The model is interesting because it is based on a combination of ABM and CA, where agents represent vehicles and traffic management centers, and the CA represents the environment where agents operate.

Regarding the workload type, either synthetic and real are employed depending on the research scenario. In certain works the experiments are performed considering geographical, environmental, and population data of specific areas, in order to investigate traffic dynamics of precise locations, while other works are not real-context-related, so that the traffic testbed is a generic environment on which to perform tests. A more complex approach is presented in [104], where a synthetic population is created according to the characteristics of the area, and the daily activity plans are generated based on data from a survey done to a portion of the population.

Discussion. Most of the reviewed papers in the area of multilevel traffic modeling rely on a micro representation of vehicles that is coupled to meso/macro models. The micro level is usually agent-based, because agents can encode arbitrarily complex driver behaviors and can interact with a faithful replica of the urban environment where important physical features can be described (e.g., morphology of the streets, presence of road-restraint devices, pedestrian crossings, speed limits, and so on). However, ABMs can be computationally demanding, so large traffic models rely on meso and macro levels wherever possible, and resort to ABMs only where "interesting" phenomena happen, such as traffic jams, dangerous interactions with pedestrians, and so on. In this regard, multiscale simulation can be viewed as a powerful alternative to downscaling, whose goal is to describe the traffic dynamics of a full city by considering only a fraction of the agents. A critical problem in multilevel traffic models is that of ensuring consistency when a level transition occurs. Traffic models employ a set of well-defined metrics such as vehicles flow across streets or junctions, average speed of vehicles, average density of vehicles and so on. These metrics must be kept consistent when switching level, a process that is made difficult by the fact that macro models are usually continuous, while micro models are usually discrete. Rounding errors must be carefully taken into account to avoid losses or creations of vehicles, that in turn might violate conservation properties.

6. Crowd mobility



Crowd modeling aims at studying how pedestrians behave in specific situations, such as *emergencies* (e.g., evacuation due to fire, earthquake), or *interaction with and other means of transportation* (e.g., car-pedestrian intersections).

6.1. Modeling approaches

Multiscale modeling is used in crowd mobility studies to achieve a suitable trade-off between computational efficiency and accuracy. At the microscopic level, the movements of pedestrians can be modeled individually in relation with the surrounding environment, since people tend to move towards the destination avoiding obstacles and excessively crowded places. To this aim, *social force models*, *centrifugal models* and *agent-based approaches* are often employed. In social force and centrifugal models, the objects in the environment have an attraction/repulsive force towards the individuals, while in the agent-based approach each individual is modeled as an intelligent and autonomous entity [105].

The macroscopic level refers to the dynamics of locally averaged quantities such as density, momentum, and energy [106]. Mesoscopic models lie somewhat between the micro and macro level, and consider groups of pedestrians disregarding internal interactions, with the purpose of modeling group dynamics while still having some form of control on single individuals [107].

Coupling between scales is generally achieved by aggregation/disaggregation of data: aggregation collects density and velocity from the micro model and inject the result into the macro level, while disaggregation generates agents at the partition boundary based on the crowd density and velocity obtained from the macro level [108]. Alternatively, both micro and macro models can simulate the same geographical area while constantly exchanging information. For instance, in [109] a synchronization module manages the parameters passing from the macro to the micro model, as the individuals follow the movement tendencies provided by the macroscopic module. Another approach is employed in [110], where the coupling of micro and macro models is achieved through aggregation/disaggregation, but the switch from macro to micro occurs only in the case some events disturb the stable movement of the crowd. Finally, in [111] the level of detail is adapted dynamically according to the execution constraints.

Finally, other simulation works in this area use a multiscale approach in order to include the effects of group dynamics, or to represent heterogeneity of individual behaviors while still having a high-level control of the pedestrian flow. Here some examples are reported. In [112], a hierarchical structure composed of crowd, groups and individuals is employed for crowd modeling, where crowd behavior is transferred from crowd to groups and finally to individuals. In [113] a set of equations describes pedestrians at the micro scale, considering attitudes such as dodging collisions, avoidance of crowded areas and group movements. On the other hand, in a macroscopic model space is represented by means of a discrete cells grid, where the density of the cells is updated at each time-step. In [114] on one level the shortest path towards the target position is computed by the A* algorithm, while another model manages steering and local collision avoidance, where agents' individualized behavior is characterized by specific (i) aversion to congestion, (ii) knowledge of map, and (iii) group membership, which define their rules of movement. Similarly, [115] proposes a multiscale framework where a *tactical* model finds the shortest paths for pedestrians towards their destination considering environmental conditions, while an *operational* model determines the movement of the agents at the micro scale, describing pedestrians' interactions in the crowd.

6.2. Emergencies

The simulation of emergency situations such as evacuation scenarios is of particular interest and a significant volume of research has been carried out to investigate them. In these scenarios a few agents called *leaders* are responsible for finding a secure exit and are followed by the others. In [116] a strategic guidance model defines how leaders with a complete knowledge of the environment seek for the exit, considering both risk and congestion, while a pedestrian-following model describes how followers behave based on the leaders' indications. Similarly, in [117] the leaders observe the environment at the macroscopic level to make strategic decisions on the route to take, while the operative aspects regarding pedestrian movements are described at the microscopic level. The leader-follower model is used in [118] to model the response to a tsunami alert: at the micro level, some agents are marked as "leaders" and represent individuals who know how to react appropriately to a tsunami alert, while the others are "followers". At the macro level, the flow of pedestrians on the road network is represented by a LWR model.

Another approach for modeling evacuation scenarios, in particular in case of fire, is to use separate models for pedestrian mobility and fire/smoke propagation. In [119] a cellular automaton describes the evolution of the blaze inside of a building, while in [120,121] smoke and fire propagation are described by a set of equations. In [122] where Markov-chain models are used to mimic both smoke propagation and people evacuation, while in [123] the authors reproduce a cinema evacuation scenario by integrating a building model with a complete city/district model to simulate daily activities in the areas surrounding the building. A similar approach is used in [124] for flood simulations, where a continuous flood model describes the spread of water over a city, while an agent-based model mimics the behavior of pedestrians heading from dangerous regions towards safe areas. In [125] the authors consider the extreme scenario of dam failure by combining an ABM that describes the process of evacuation of people taking into account the heterogeneity of individual behavior and social characteristics, and a hydrodynamics model based on diffusion equations. Both levels are kept synchronized: the hydraulic simulation is executed first, and the results are integrated into the ABM. It is worth observing that the temporal scale of the models is different (10 minutes vs 5 seconds), so that the water depth is updated only after 120 steps of the evacuation model.

Fluid dynamics can also be employed to simulate the movement of individuals in conditions of overcrowding, which is typical during evacuation or concerts. In [126] the authors integrate an ABM with Smoothed-Particle Hydrodynamics (SPH), a method where fluids are represented as a collection of particles that interact with each other according to a set of physical laws. To couple the two components, each agent is treated as a SPH particle subject to various types of forces that ultimately drive the speed and acceleration of agents.

In [127] the physical space in the evacuation model is either continuous or represented as a network. A continuous space representation is used for regions where a fine-grained resolution is necessary: in these regions it is possible to have a sophisticated description of pedestrians' behavior, with different types of agents reacting in different ways to the stimuli of the environment. Each agent is described by a set of continuous attributes such as position, velocity, body frame width, and others. In regions where a high level of detail is not required, a network approach is used where naturally occurring partitions such as rooms or corridors are graph nodes, and doorways or other forms of connectivity are edges. Nodes and edges have a capacity defined as the number of people that a space partition can contain and the maximum number of agents that are allowed to traverse an edge on a given time.

6.3. Interactions with other means of transportation

Simulation of pedestrians might be combined with models of other means of transportation in order to analyze the interactions between them. For instance, in [128] the authors investigate railway crossing intersections, using a discrete-event model to represent pedestrians and a continuous model to represent trains. In [129] the risk of collisions between vehicles and pedestrians at road intersections is evaluated with a multilevel modeling approach, considering both micro-environment factors (e.g., the characteristics of the intersections such as traffic signs, vehicles flow, road features and crosswalks) and macro-environment factors such as the urban design and land use of the areas surrounding the intersection. In [130] a queueing network model simulates vehicular traffic, public transport and pedestrians in low-density conditions, while movement of pedestrians under dense conditions is described by a force-based model.

In [131] the purpose is to simulate crowd behavior in the context of public events. While a macroscopic model describes the arrival of people via shuttle bus, the movement of pedestrians inside the event areas is modeled at three different levels: *strategic* to define the target of the individuals, *tactical* to determine the route towards the destination and *operational* describing the actual walking behavior. Operational level is described at either microscale (for cramped and narrow areas) or mesoscale via a cellular automaton model, with transition zones managing the scale switching.

Although agent-based models are the most frequently used approaches for crowds simulation, cellular automata are used as well. In [132] a cellular automaton represents people movements inside the two ferry terminals, while a mesoscopic graph-based model simulates the journeys of ferries.

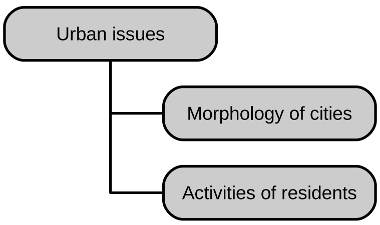
Discussion. Multilevel modeling of crowd mobility shares some methodological patterns with traffic modeling (Section 5). Indeed, in both areas it is common to have an ABM that describes entities at the micro level, and equation-based models to deal with aggregate metrics like density, flow and average speed at the macro level. However, studies in crowd mobility differ widely in purpose; for this reason, the description of the movement of pedestrians is combined with the specification of other aspects of the system, such as the propagation of smoke and fire in the context of evacuation from buildings. Additionally, the physical space considered in crowd models is usually significantly smaller than a whole city, which on the other hand is the typical of traffic simulations. As

Table 4
Papers on traffic modeling (ABM = Agent-Based Model, CA = Cellular Automata, DES = Discrete-Event Simulation, LWR = Lighthill, Whitham and Richards, SPH = Smoothed-Particle Hydrodynamics, ODE = Ordinary Differential Equations).

Paper	f	Methodology
[108]	crowd in dynamic environments	micro CA model + macro model
[109]	evacuation	macro continuum model + micro CA model
[110]	crowd behavior	macro flow-based model + micro ABM
[111]	crowd in urban environment	hierarchical adaptive model
[112]	crowd behavior	crowd, group and individual level
[113]	crowd behavior	ODE-based micro and macro models
[114]	crowd behavior	global path panning (A*) + local collision avoidance
[115]	movements of pedestrians	operational level + tactical level
[116]	evacuation	evacuation and strategic guidance ABM + cell transmission-based pedestrian-following model
[117]	evacuation	strategic level + tactical level + operational level
[118]	evacuation	micro agent-based model + LWR
[119]	evacuation	fire and smoke propagation (cellular automata) + pedestrians model (intelligent agents)
[120]	evacuation	smoke model + fire model + multiscale pedestrian mobility model
[121]	evacuation	fire, smoke, heat, and pedestrians models
[122]	evacuation	fire propagation + people evacuation
[123]	evacuation	cinema model + city model
[124]	evacuation	flood model + agent-based crowd model
[125]	evacuation	evacuation model + hydrodynamics model
[126]	overcrowding	ABM + SPH
[127]	evacuation	continuous and network space representation
[128]	train-pedestrians intersections	continuous train model + DES pedestrians model
[129]	pedestrian-vehicles collisions	micro-environment factors (in the vicinity of intersections), macro-environment factors (urban design, land use of neighborhood)
[130]	evacuation	queue model + force model
[131]	crowd at events	public transport level + (multiscale) event site level
[132]	crowd at ferry terminals	cellular automaton (micro) + graph model (macro)

a result, cellular automata turn out to be particularly well suited for representing pedestrians moving inside buildings or small portions of urban locations, since they provide an appropriate combination of expressiveness and computational efficiency. Finally, the movement of pedestrians is often less constrained than that of vehicles, since individuals can more easily adapt their route depending on the environment. Thus, crowd models frequently employ an additional layer where medium-term decisions on the path to follow are taken.

7. Urban issues



Investigations on urban issues include topics concerning the *morphology of cities* and the *activities of their residents*.

7.1. Morphology of cities

Nowadays, it is increasingly important to take environmental issues into account during urban planning. Climate change may increase the probability of occurrence of dangerous events such as floods, droughts or excessive heat. In [133] the authors provide a Urban Integrated Assessment Framework (UIAF), with the aim of evaluating the impact of the climate and economic change over the cities. UIAF comprises a set of models that are coupled according to a three-level hierarchy. At the top, city models consider socio-economic changes and climate forecasts to analyze spatial patterns of a future population. City-zonal models downscale the above data to a finer spatial resolution, in order to estimate climate-related impacts using population, transport and land-use models. Finally, zone-parcel models enable the simulation of the possible spatial pattern of housing development associated with the population prediction for each zone.

The paper [134] deals with the problem of heat islands, i.e., urban areas that are significantly warmer than their surroundings. Three types of models are used at different spatial scales; they consider different types of parameters such as temperature, wind (for mesoscale), greenery, surrounding buildings, and pavement (for microscale).

Other works deal with urban planning, trying to help to evaluate the possible impact of new policies and infrastructures changes. Simmobility [135] is a simulator that integrates various mobility-sensitive behavioral models, allowing for analyses that consider land use, transportation and communication interactions. The software allows three time resolutions, from fractions of seconds for the short-term scale to days or even years for the long-term resolution. Long-term scale is used to represent strategic activities, such as job or house relocation, land development or the purchase of a vehicle. On the other hand, mid-term level represents daily activity scheduling, route, destination and departure time choices, encompassing a pre-day model (i.e., a model for deciding the daily schedule of an agent) and a within-day model (i.e., model for transforming the activity schedule into effective decisions and execution plans). Finally, short-term scale takes care of traffic and pedestrian mobility, modeling the movements of people, vehicles and commodities.

Some papers have a specific focus on urban planning, such as in [136] and in [137], where city expansion dynamics are simulated considering respectively the use case of Wuhan and Auckland. In [136] the development process of an urban area is simulated by a three-scale framework: a macro SD model to predict the demand of new urban land use, a meso model to take into account intercity interaction to determine the areas for potential urban expansion, and a microscale model to represent neighborhood interactions through logistic regression. The three scales are then incorporated to form a cellular automaton describing the evolution of the land use in the region. In [137] *government agents* manage the urban development at the macroscale according to zonal requirements and the needs of *resident agents*, which try to find the best place to live at the micro level. The ABM is then coupled with an artificial neural network for supporting agents' decisions about which non-urban zones to consider for city expansion.

Studies on the potential urban growth of the city of Wuhan has been carried out in [138] through a multiscale hierarchical framework. At the macro level the probability of change is defined in the whole study area, at the meso level the density of change is defined only in the extent of land-cover change from non-urban to urban, and at the micro level the intensity of change defines locally the extent of the changes. Similarly, in [139] the authors present a modeling framework with the goal of reproducing the processes of land use/cover change in Costa Rica. A system dynamics model uses data at different aggregation scales, showing how local, regional and national trends can actually have opposite effects and results.

Finally, some research works use a pure ABM approach for describing land-use dynamics. In [140] cellular automata are employed both at macro level to simulate land use and transport infrastructure, and at the micro level to reproduce pedestrians' movement. In [141] the authors combine different agent-based sub-models describing how environmental, social, and economic factors change the land-use dynamics. Sub-models interact according to the concept of "co-modeling", which means that micro models are considered as agents of higher-level models.

7.2. Activities of residents

In [142] air pollution is analyzed considering the urban scenario of Madrid. Computational Fluid Dynamics (CFD) models are employed to reproduce PM_{10} dispersion. The outputs of other models are used to feed CFD with appropriate inputs. Specifically, the Weather Research and Forecasting (WRF) mesoscale model provides boundary conditions for what concerns meteorological variables such as wind speed and direction and surface heat fluxes, while a microscale traffic emissions model provides hourly PM_{10} emissions.

In [143] a regional regression model is combined with a local agent-based model to describe deforestation processes in Amazonia. The macro regression model considers various environmental, demographic, agrarian structure, technological, and market connectivity indicators, while at the local scale two types of agents exist: small farmers who prefer lands close to roads or urban centers and big farmers who look for large pieces of inexpensive land. Land use research has also been carried out through multilevel regression techniques. For instance in [144] the authors constructed a predictive statistical model to investigate over land use in Philippines, considering data at field level (i.e. type of cultivation and characteristics of the land), household level (i.e. ethnicity of family components) and village level (i.e. percentage of the population with a certain origin).

Some works are dedicated to issues concerning smart territories, which is a topical subject due to the recent advent of Internet Of Things (IoT) applications. In [145] human mobility is integrated in a simulation of IoT and smart territories, focusing on a smart market scenario where users can subscribe their interests to some products or services, receiving information about events and sales in the neighborhood. In this work, two simulators are employed at two different levels of detail. At a coarser level an agent-based simulator uses PADS and DES methodologies to describe dynamics over the whole territory, with agents being involved in sales, subscriptions, and geographical movements. On the other hand, a fine-grained simulator can be triggered when needed in order to describe in detail the specific interactions within the smart market, considering wireless communication issues, interactions and movements. In [146] a further level is added, with a set of equations describing the flow of customers and the parking strategies in the neighborhood. Here a wrapper is used to handle the interactions among the models, coordinating the execution of the two fine-grained simulators and synchronizing their activities with the higher-level simulator. Parking activities have also been studied in [147], where an NFD model describes the vehicle flow, while at the microscale a parking algorithm mimics cruising-for-parking activities. In this model the decisions are influenced by factors like cruising speed, parking duration and, of course, parking occupancy.

On a slightly different topic, in [148] the spread of black rats by means of commercial transportation in Senegal have been studied. The modeling approach is based on the concept of *world*, a complete and self-sufficient sub-model with its own places,

Table 5
Papers on urban issues (ABM = Agent-Based Model, CFD = Computational Fluid Dynamics, NFD = Network Fundamental Diagram, WRF = Weather Research and Forecasting).

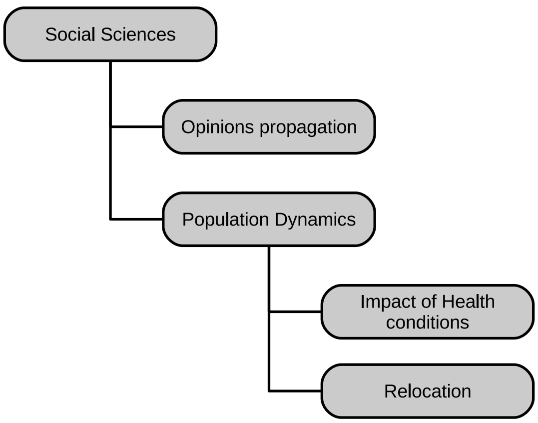
Paper	Theme	Methodology
[133]	flooding	socio-economical, city-zonal and zona-parcel models
[134]	urban heat islands	micro, meso and macro model
[135]	urban environment	short-term, mid-term and long-term activities models
[136]	land use, urban expansion	multiscale ABM + artificial neural network
[137]	urban expansion	micro, meso and macro model
[138]	urban expansion	micro, meso and macro model
[139]	land use	local, regional and national scale
[140]	urban planning	macro level (land use and transport infrastructure + micro level (pedestrians' movement)
[141]	land use	ABMs at environmental, social and economic level
[142]	urban pollution	CFD + WRF models
[143]	land use	regional regression model + local ABM
[144]	land use	multilevel regression model
[145]	smart territories	coarse-grained smart territory model + fine-grained smart market model
[146]	smart territories	coarse-grained smart territory model + fine-grained smart market and parking model
[147]	parking activities	NFD model for traffic flow + micro parking model
[148]	spread of black rats	nested self-sufficient sub-models

agents, spatial resolution and temporal scale. The agents are either rats or humans transporting them, so that they can travel through different locations. Worlds may be provided with *gates*, which are discrete-space cells that act as crossing points in common with other worlds, enabling the switch of an agent through different worlds. Important factors for determining the outcome of a simulation are human mobility and rat reproduction dynamics. While humans can travel towards a limited set of destinations with certain vehicles, the suitability of the environment for the rats depends on space information such as bioclimates, types of terrain, etc.

Discussion. The research area dealing with urban issues is probably the most diversified among those that we have considered; this is reflected by the wide variability of aim and scope of the papers that have been discussed in this section. It is therefore difficult to identify common methodological patterns; however, the majority of the reviewed works share a common trait, that is, the use of real geographical data as opposed to randomly generated scenarios. Indeed, when studying urban issues related to existing cities it is crucial to mimic the environment under test as accurately as possible, in order to carry out experiments on real-world scenarios. Synthetic data might still be employed when performing "what-if" analyses, i.e., to study how the urban environment would react to different situations.

We observed that studies in urban issues, by their very nature, rely heavily on techniques and tools that have been developed in the context of mobility and traffic modeling. Due to the many aspects that must be taken into account in certain urban studies (e.g., pollution, land use), the cooperation among semantically different models is important.

8. Social sciences



Models used in the social sciences differ significantly in purposes and implementations; however, a common trait is that the dynamics of individuals are considered in relation to other individuals or groups. To avoid excessive fragmentation, we discuss all the relevant works in this section; indeed, despite the large variability there are some recurrent common elements, regardless of the specific research area within the social sciences community.

Since human relations are of different types, a frequent approach is to use multilayer graphs for modeling social relationships: nodes represent individuals, edges connections between them and the layers are the various environments where specific connections occur. This methodology is popular, e.g., for investigations concerning the diffusion of trends, news and ideas, since multilayer graphs are well suited for representing information over multiple social networks which individuals may belong to.

For instance, in [149] two separate layers are employed to represent Twitter and FriendFeed links. Similarly, in [150] two layers represent two types of human relationships, and a SIR-like model is used to mimic information propagation, where individuals are either unaware of the information, or spreading the information to the contacts, or no longer spreading information. In [151] different layers correspond to different types of relationship. A multiplex network (i.e., multilayer network where inter-layer edges can only connect nodes that represent the same actor) is used to investigate society structuring, proving the hypothesis that society is composed of several strongly-tied communities which are in turn connected to each other by weak connections.

In [152], online and "real-life" connections are represented in different network layers, while information propagation is described through a compartmental model where people are either *Ignorant*, *Spreader*, *Variation* (people who diffuse an altered version of the information), *Oyster* (people who received information but are not actively spreading it) or *Recovery* (people who no longer spread information) [153].

In [154] Twitter data is used to investigate retweet dynamics, in order to look at how information spreads through social media platforms. In this work three levels are considered: (i) potential-retweeter-level variables include attributes capturing the features of the potential retweeters and their connections with the topic of the tweet (e.g., interest similarity), (ii) parent-level variables include cascade depth, and (iii) cascade-level variables include attributes such as the content characteristics and popularity of the tweet.

A second significant research area in the field of social sciences is *population dynamics*, involving issues such as predisposition to diseases, homophily, migration and gentrification. The latter refers to the influx of middle-class or wealthy people in popular neighborhoods, causing the rise of prices that makes it difficult for low-income residents to cope with the new cost of living. To model these scenarios accurately it is important to collect reliable data, which are then analyzed at both the individual and aggregate level, to find useful insights supported by statistical evidence.

Several works have been carried out following this approach. A first category of papers is dedicated to finding *links between health conditions and individual characteristics*. In [155] childhood obesity is analyzed by considering information at individual level (sex, age, ethnicity), zip-code level (median household income, lifestyle classifications, urbanization), county level (median household income, urban-rural distribution). In [156] the authors study correlations between obesity and diabetes, taking into account the characteristics of both individuals and the geographical area (e.g., poverty, population density). In [157] malaria diffusion in children is analyzed considering risk factors at individual level, household level (wealth, education, sources of drinking water) and community level (place of residence). In [158] the incidence of visceral leishmaniasis in the Brazilian city of Teresina is studied census tract level (socio-economic and demographic information) and district level (prevalence canine infection, and insecticide spraying). In [159] the intent is to evaluate the efficiency of "Avahan", a HIV prevention program in India, taking into account variables at both individual and district level. In [160] a multiscale geographic weighted regression model has been employed to link economic and social indicators to road fatalities in Texas. From this investigation, it turned out that one of the most important factors associated with road accidents at the local scale is the average time required to go to work, while at the regional and global scale one of the most concerning factors is driving alone, which has a negative effect on road security. In [161] the authors analyzed the role of socio-economic and environmental influence on food choice, and specifically on fruit and vegetables consumption. This study considers data at both individual level (survey data on fruit and vegetable consumption, individual and social influences) and neighborhood level (supermarket and fruit and vegetable store density). In [162], the authors investigate how the sexual orientation affects the earnings of US citizens, considering data at both individual level and contextual level (i.e., the presence or absence of a state-level anti-discrimination laws, and which political party was governing the state during the considered period).

A second category of papers analyses the effects of *relocation* of individuals. In [163] gentrification phenomenon is studied considering as a use case the city of Philadelphia. The model takes into account features both at (i) individual level, such as ethnicity, education attainment, marital status and income and at (ii) neighborhood level, such as the gentrification process of a local area and neighborhood stability. Similarly, in [164] correlations between gentrification and voter turnout are investigated examining the Atlanta social scenario. In this work, the authors consider variables at individual level (age, gender, ethnicity) and neighborhood level (average instruction level, gentrification rate, percentage of owner-occupied housing units), while also taking into account cross-level interactions between gentrification and longstanding voters. In [165] a multilevel modeling approach is proposed to analyze the migration phenomenon within Norway. In this work various approaches are proposed, considering both individual and aggregated features such as age, job, family status, education level, etc., which define individual probabilities of migration. The paper proposes models of different complexity, culminating with the event history models, where decisions are carried out based on data about the events that occurred throughout the entire life history of the individuals. Slightly different is the approach adopted in [166] to model social integration of migrant workers in China, where a two-level data structure is employed, considering both individual and city level. Similarly to other works, individual variables include demographic, social, and occupational characteristics of migrants, while city variables concern the nature of a city, economic conditions, population structure, language and culture, and institutions. In [167], a study on human mobility considers features at the micro level (household and housing units), meso level (groups of micro-agents and urban-sectors) and macro level (city characteristics, urban planning), where people mobility is influenced by agents similarity and affinity between social groups and urban sectors. Studies on population are not necessarily

Table 6
Papers on social sciences (ABM=Agent-Based Model, CM=compartmental model, IBM=Individual-Based Model, LR=logistic regression, MG=multilayer graph, SD=System Dynamics).

Paper	Theme	Type	Levels/Layers
[149]	social networks	MG	Twitter layer + FriendFeed layer
[150]	information diffusion	MG	each layer corresponds to a different type of relationship
[151]	society structuring	MG	each layer corresponds to a different type of relationship
[152]	information propagation	MG	internet layer, real-life layer, and intermediate cognitive transition layer
[154]	retweet dynamics	MG	variables at parent level, cascade level, and potential retweeter level
[155]	childhood obesity	LR	individual, zip-code, county and state level
[156]	obesity and diabetes	LR	individual and geographical level
[157]	malaria in children	LR	individual, household and community level
[158]	incidence of canine infection	LR	census tracts and district level
[159]	impact of AIDS prevention programs	LR	individual and district level
[160]	road security	LR	local, regional and local scale
[161]	women's diet	LR	individual and neighborhood level
[162]	economic discrimination	LR	individual and contextual level
[163]	gentrification	LR	individual and neighborhood level
[164]	gentrification	LR	individual and neighborhood level + cross-level interaction
[165]	migration	LR	individual and aggregate level
[166]	migration	LR	city and individual level
[167]	population spatial evolution	ABM	buildings, urban sectors, and city level
[168]	poikilotherm-structured population	IBM + CM	egg production, population dynamics
[169]	predator–prey	IBM + SD	micro + macro

limited to the human species. For instance, in [168] the authors study *poikilotherms* (animals whose internal temperature varies considerably, e.g., lizards) with the goal of estimating mortality and fecundity rates. In the proposed approach, an individual-based model (i.e., a model that simulates populations as being composed of discrete individual organisms) predicts the number of produced eggs based on the current adult population, while a compartmental model describes population dynamics through the means of a set of ODEs.

Lastly, in [169] a multiscale approach is proposed for social sciences analyses based on the well known prey/predator model [170]; the variation in the number of predators and prey is defined by differential equations at the macro level, while the micro model is in charge of describing individual behavior of both preys and predators.

Discussion. The methodology used in the scientific literature dealing with multilevel modeling of social sciences differs remarkably from that used in the other areas considered in this review. For example, in the social sciences it is typical to use the term "level" to denote a point of view of the system rather than a component of a model. ABMs are very popular in the social sciences [171], even if they are not frequently employed in multilevel frameworks. However, we believe that multiscale approaches could become increasingly relevant in the future, as the recent development of multiscale ABMs platforms such as LevelSpace [172] could boost the use of this methodology. LevelSpace is an extension of NetLogo [173], a widely used tool for implementing agent-based models. Through LevelSpace, developers can develop applications composed of multiple interacting NetLogo models that are structured hierarchically, facilitating the creation of multilevel simulators and the integration of existing models.

9. Others

In this section we discuss the papers that did not fit into any of the other categories.

In [174] a supply chain simulation framework is presented. Although most of the works in this area use discrete-event models, the paper proposes a multilevel methodology that uses both continuous and discrete models. The activities of a company are modeled at different scales, with the operational level describing activities in singles plants over a short-time horizon, while tactical and strategic levels describe high-level policies. The components of the system are either continuous or discrete; specifically, information about customer orders and supply chain components are considered as continuous variables, while transportation is discrete.

The goal of [175] is to quantify the economical impact of climate change on different stages of the potato supply chain, considering issues such as drought and extreme weather. The investigation is performed through a pure agent-based approach, with five levels appearing in the simulation: the cultivation, shipping and processing of potatoes, the retailing and the logistics of the transportation of commodities. A machine learning model is also integrated in the simulation for predicting potato prices, taking into account yearly trends and seasonality.

In [176] an agent-based modeling framework with multiple temporal scales is used. The model represents the agents involved in the process of producing, consuming and distributing commodities (i.e., establishments and freight vehicles drivers). The proposed framework is composed of three time scales: long-term planning represents strategic activities such as commodity flows and logistic network formation, mid-term planning represents tactical decisions such as shipment generation, logistic planning, and vehicle flows, and finally short-term planning represents operative choices, such as scheduling, routing and dispatching decisions.

Table 7
Papers on topics not included in those above (ABM = Agent-Based Model, SD = System Dynamics).

Paper	Theme	Methodology
[174]	supply chain	operational, tactical and strategic levels
[175]	supply chain	ABM
[176]	logistic	short-term, mid-term, and long-term planning models
[177]	market	ABM + SD
[178]	emotional psychology	mood, emotion and character layer

Table 8
Most frequently used methodologies within each research area.

Application Area	Methodology
Local epidemic diffusion	Within-host model + Between-host model
Global epidemic diffusion	Large-scale mobility model + Local between-host models
Traffic	Macroscopic model + Microscopic model
Crowd behavior	Macroscopic model + Microscopic model
Crowd evacuation	Smoke/fire model + Microscopic model
Population Dynamics	Multilevel logistic regression model
Information diffusion	Multilayer graph

In [177] the authors propose a simulation environment that combines agent-based modeling and system dynamics, taking a two-company marketplace as example. At a high level, information collected from the behavior of individual agents (i.e., customers) is aggregated to describe trends. Customers are influenced by high-level information such as the popularity of a product; customers are also influenced by the decisions of their customers according to a neighborhood model. From the companies' point of view, the capacity to attract and retain customers is modeled by continuous feedback loops according to a SD approach. Fundamental elements for the described framework are the Continuous Agent-Based Modeling (CABM) Builder, which takes the inputs from the agents to build the equations to be solved, also handling the neighborhood model and the CABM solver, which solves the various equations to compute the simulation results.

Finally, in [178] a multilevel approach is used to study emotional psychology: the authors propose a model that maps the interactions among mood, emotion and characters, which are defined on three different levels and with a set of equations, into changes in mood and emotion.

10. Discussion and conclusions

In this paper we performed a systematic literature review of multilevel modeling of human mobility and behavior. Multilevel modeling provides several benefits, such as the possibility to choose an appropriate trade-off between precision and efficiency, and better code organization that leads to faster development and improved maintainability. Simulations involving human mobility naturally lead to a multilevel approach, since interactions happen at both a local scale (individuals) and a global scale (population). Indeed, our survey shows that the number of papers using multilayer/multilevel modeling applied to human mobility and behavior is increasing.

The survey examined 125 research works, mainly conferences and journal papers, from which five application areas have been identified: epidemic modeling, traffic modeling, crowd mobility, urban issues, and social sciences applications. The review has been organized around these application areas, to uncover which modeling patterns are most frequently used within each area. To ensure transparency and completeness, raw data of the papers considered in our review are available[2].

Table 8 summarizes the recurrent patterns that we have identified; in some cases, different techniques are used within sub-areas. Research works dealing with epidemic spreading make frequent use of a combination of within-host and between-host models, which are a natural way to describe the diffusion of a pathogen inside the human body (within-host) and across individuals (between-host). At a larger scale, global epidemic diffusion makes use of mobility models to account for human mobility. On the other hand, traffic modeling and crowd mobility studies use microscopic models to accurately describe the behavior of a single individual, combined with macroscopic models to describe flows of vehicles or crowds. To analyze emergency scenarios such as crowd evacuation due to flood or fire/smoke, microscopic models are integrated with water or fire propagation models because the behavior of each individual is driven by the level of perceived danger in its surroundings. Population dynamics studies are typically based on multilevel continuous models. Finally, multilayer graphs are the tool of choice for studying information diffusion.

Fig. 7 classifies the modeling simulation approaches for epidemic diffusion according to two dimensions: the type of models used (continuous, discrete, and mixed), and the level of detail (low, high, mixed). In both cases, "mixed" refers to the case where the models used at different levels are of different types.

Fig. 8 shows the same classification for simulation approaches for crowd and traffic modeling; other application areas use a more varied combination of approaches, and therefore such a classification is not possible.

[2] https://pads.cs.unibo.it/doku.php?id=multiscale

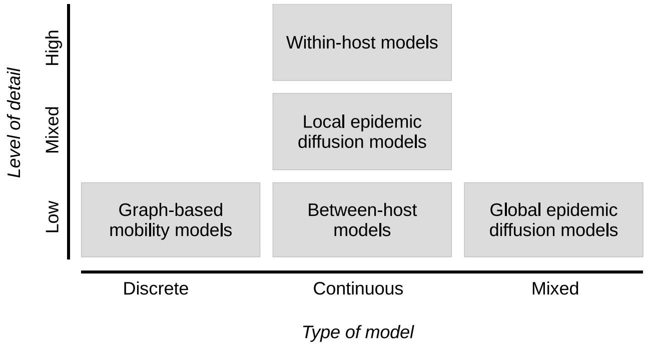


Fig. 7. Classification of M&S approaches for epidemic modeling.

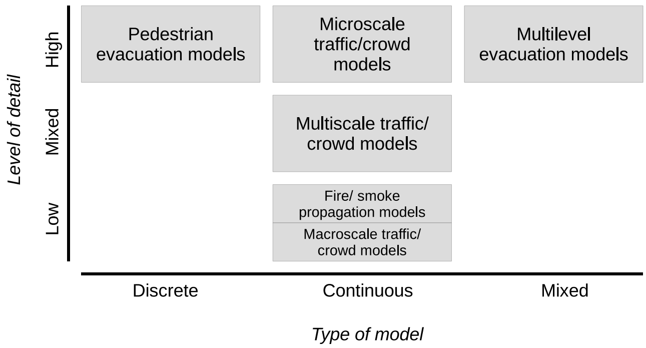


Fig. 8. Classification of M&S approaches for crowd and traffic modeling.

Table 9
When to use multilevel, multiscale, or multilayer M&S.

Requirements	Models
Different types of relationships between entities	Multilayer models
Semantically different components, or availability of existing models	Multilevel models
Trade-off between accuracy and execution time, or required coarse and detailed models	Multiscale models

It turns out that there are several recurrent patterns regarding model linkage, i.e., some common techniques to let models at different levels exchange state information. In some cases, each level provides parameter values that are used by the other levels. For example, in epidemic modeling the outcome of an infection within individuals, as determined at the within-host level, produces the contagion probability that can be used at the between-host level to analyze the diffusion on a large scale. In turn, the probability that a healthy individual comes into contact with an infected one depends on the large-scale diffusion of the epidemic, and may trigger an infection depending on the result of the within-host level. Another common approach for exchanging information between levels is the aggregation–disaggregation of variables. This is typical, for example, in traffic and crowd simulation, where aggregate values (e.g., the average speed or density of a crowd) are passed to the macro level (aggregation), which in turn provide parameters that are instantiated, possibly with some random variations, on individuals at the micro model (disaggregation).

The last important point that has been observed during the review refers to the accuracy and reliability of models. This is a cross-cutting concern that is common to all modeling studies, regardless of the application domain and/or the employed technique, and can be summarized by the motto “garbage in, garbage out”. While multi-level modeling and simulation allows to address part of this issue by enabling developers to choose the most appropriate level of detail when and where needed, the problem of choosing realistic parameters and workloads remains. Social science models have data at their core, thus for such studies data collection is particularly important. On the other hand, epidemic investigations might use parameters such as infection and recovery rate based on real data from territories, coupled with a mobility sub-model that rely on actual data on people movements among different regions. Traffic and crowd simulations, on the other hand, often combine synthetic information with real data such as road features, geography of the area and human presence. In any case, the importance of proper workload characterization and validation could never be emphasized enough.

In Section 2 we have discussed the difference between multilayer, multilevel and multiscale modeling and simulation. Having completed the review of the scientific literature, we can summarize in Table 9 the most common reasons to use each of these modeling techniques. We observed that *multilayer* models are frequently used where there are different types of relationships between entities, such as models that describe information propagation where each layer represents different types of social networks. *Multilevel* models are used when it is necessary to integrate multiple existing models – possibly with different semantics – in a single simulator, e.g., evacuation models where a component represents the spread of smoke and fire, and another component reproduces the behavior of pedestrians. Finally, *multiscale* models are appropriate where it is necessary to identify an appropriate trade-off between accuracy and efficiency, e.g., traffic models where only the critical parts (city centers, congested roads) are characterized by a fine-grained representation.

Data availability

Data and information about the reviewed papers are linked in the manuscript

Appendix. Acronyms

ABM Agent-Based Model

ARZ Aw–Rascle–Zhang

CA Cellular Automata

CABM Continuous Agent-Based Modeling

CFD Computational Fluid Dynamics

DES Discrete-Event Simulation

IDM Intelligent Driver Model

IoT Internet Of Things

LWR Lighthill, Whitham and Richards

NaSh Nagel–Schreckenberg

NFD Network Fundamental Diagram

ODE Ordinary Differential Equations

PADS Parallel and Distributed Simulation

PDE Partial Differential Equation

PW Payne–Whitham

SD System Dynamics

SEIR Susceptible-Exposed-Infected-Recovered

SIR Susceptible-Infected-Recovered

SIS Susceptible-Infected-Susceptible

UIAF Urban Integrated Assessment Framework

WRF Weather Research and Forecasting

SPH Smoothed-Particle Hydrodynamics

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