

Integrating agent-based modeling and dynamic lca: an environmental impact simulation and optimization model for dormitory buildings

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Abstract

The interactions between dynamic factors are often overlooked in dynamic life cycle assessment (DLCA), and the effectiveness of optimization solutions guided by assessment results is difficult to quantify. Therefore, this study embeds DLCA elements into the agent-based modeling (ABM) to develop an integrated model for buildings. The model simulates the dynamic interactions between external environment, building system, and occupants, and incorporates a feedback mechanism to guide optimization based on assessment results. A case study of dormitory buildings demonstrates the model's applicability and quantifies the effects of optimization strategies. The results indicate that ignoring the interactions between dynamic factors can lead to assessment deviations of up to 2.26×10^5 units, and the proposed optimization strategies are able to reduce the cumulative environmental impacts by 5.8%. This study explores the deep integration of ABM and DLCA, and simulates the interactions between dynamic factors, improving evaluation reliability and enabling timely guidance of optimization strategies.

1 Introduction

In the global warming context, buildings are major contributors to environmental strain. According to the International Energy Agency, building operations account for 30% of the global energy consumption and 26% of the global energy-related emissions. In China, the building sector accounts for approximately 30% of national total energy consumption [1]. High energy use in buildings leads to substantial pollutants, including CO₂, SO₂, and N₂O, which imposes significant environmental burdens. In response, the Chinese government has introduced a series of policies, such as the 14th Five-Year Plan for Building Energy Efficiency and Green Building Development and the Action Plan for Accelerating Energy Conservation and Carbon Reduction in the Building Sector. Accordingly, it is imperative to scientifically evaluate and effectively manage the environmental impacts of buildings.

Life cycle assessment (LCA) provides a comprehensive and systematic framework for assessing the environmental consequences of a product/service. It can reliably assess environmental burden and has become a key tool for evaluating the environmental impacts of buildings. To support LCA practice, research institutions worldwide have established some inventory databases, such as the Swiss Ecoinvent, European Reference Life Cycle Database, and Chinese Life Cycle Database. Moreover, some building-specific LCA software has been developed to facilitate application, including Building for Environmental and Economic Sustainability, Athena, and ECOSOFT. LCA has been widely used in the comparison of multiple building design options [2], selection of building components [3], evaluation of construction activities [4], analysis of operational carbon emissions [5], and management of building waste [6].

In the past years, the LCA studies have gradually shifted from traditional static ones to temporally dynamic assessments that comprehensively consider the potential dynamic variations in the long-term cycle of a building [7]. Dynamic LCA (DLCA) is regarded as the latest developmental direction and an important trend in the environmental management field. Up to now, some feasible DLCA models for buildings have been established. The dynamic matrix model [7], the data transformation-based model [8], and the "static framework + dynamic variables" model are typical ones [9]. Various dynamic factors have been identified, and their temporal variations have been described and incorporated into assessment. The most frequently examined dynamic factors include occupant behaviors [9], energy evolution [10], climate change [11], and weighting factors [12]. Dynamic

assessment results have demonstrated that DLCA is more accurate, comprehensive, and flexible than the static one [13]. Currently, although DLCA studies in the building field have made significant progress, two major limitations still exist.

Limitation 1: Less consideration of interactions between dynamic factors

Previous DLCA studies usually introduced dynamic factors independently into assessments, ignoring the fact that these dynamic factors can interact with each other and that their interactions may also be time-dependent [14]. In fact, the environmental impacts generated by a system are jointly shaped by the interactions between various dynamic factors. For example, climate change can influence occupants' perception of thermal comfort, thereby influencing their energy use behaviors [15]. The degradation rate of household appliance is not only determined by their service life but also by outdoor temperature and humidity conditions [16]. Ignoring the interactions between dynamic factors can oversimplify the system's actual evolution, creating significance discrepancies between assessment results and real-world conditions, and thereby compromising the reliability and decision relevance value of assessment results. Explicitly incorporating the interactions between dynamic factors into the DLCA framework not only improves the accuracy of the assessment results, but also enhances DLCA's capability to capture and interpret complex real-world systems. Addressing this research limitation is essential for fully realizing DLCA's potential as a robust decision-making tool for sustainable practice [17].

Limitation 2: Less involvement of optimization

Currently, most DLCA studies typically focus on capturing the temporal variations in dynamic factors, and their assessment results are mainly used to analyze the temporal trends in environmental impacts. In these studies, data flows exhibit a unidirectional pattern, where temporal dynamic factors are provided as input, and assessment results are output directly [18]. The effects of different optimization strategies are seldom embedded in the DLCA assessment process, and their potential environmental benefits are often presented after they have been implemented [19]. This limitation usually confines DLCA to a purely evaluation tool in practical applications, failing to fully realizing its potential to guide environmental management. Incorporating the effects of optimization strategies as feedback within LCA can establish a bidirectional data flow between decision variables and environmental impacts. This enables the quantification and analysis of optimization strategies under dynamic scenarios and has been recognized as a promising research direction [20].

To address these two limitations, this study integrates agent-based modeling (ABM) and DLCA method in building scenarios. An integrated model is developed to simulate the interactions between dynamic factors and to embed optimization-driven management strategies through a feedback loop. This paper is organized as follows: Section 2 reviews building DLCA research, ABM studies, and LCA and ABM integration; Section 3 introduces the ABM-DLCA methodology; Section 4 conducts a case study in dormitory buildings and analyzes assessment results; Section 5 presents some discussions; and Section 6 draws the conclusions.

2 Literature review

2.1 Dynamic factors in building DLCA research

In the past decade, many DLCA studies have been conducted in the building field, including methodology research [21], case studies[22], and comprehensive reviews [7]. The dynamic factors involved in current DLCA

research can be generally classified into three levels: external environment, building system, and occupants [9]. At the external environment level, factors such as temperature and resource availability have gained much attention. For instance, Brambilla et al., (2018) [23] found that temperature changes affected indoor heating and cooling energy consumption. Phillips et al., (2022) [15] investigated the influences of climate change on occupant comfort and then assessed the dynamic greenhouse gas emissions of office buildings.

At the building system level, possible dynamics in building envelope, technological advancement, and maintenance practice have been increasingly investigated. Su et al., (2017) [22] noted that the technical performance of equipment deteriorates over time, resulting in increased energy consumption. Pauliuk et al., (2013) [24] showed that the refurbishment of building equipment could reduce environmental impact by 30%–40%. Scholars have recognized that considering changes in building system is helpful to obtain more representative evaluation results.

Occupants play an important role in buildings' operational energy and emissions and dynamic factors at the occupant level have drawn much attention in the last decade. Negishi et al., (2018) [9] pointed out that changes in occupant characteristics and behaviors, such as occupancy schedules, thermal comfort preferences, and occupation duration, could significantly influence energy consumption.

2.2 ABM-LCA integration

ABM is a computational simulation framework that models autonomous agents based on complex system theory. It operates in a stochastic environment using computer language. Agents communicate, cooperate and even compete with each other according to their attributes and behavior rules [25]. This approach has been widely adopted in many industries.

In the construction field, ABM has been employed to understand and optimize building performance and occupant behaviors. Uddin et al., (2022) [26] adopted ABM to assess how different interior designs affect occupants' lighting usage patterns, thereby impacting overall energy consumption. Jensen et al., (2016) [27] applied ABM to evaluate the relationship between households' ventilation behaviors and heating energy demand. These studies demonstrated the potential of ABM in identifying energy-saving opportunities by modeling occupant behaviors.

Based on this characteristic, ABM has been increasingly regarded as a useful tool for generating behavior-driven consumption data, which can be further used as foreground inventory data for LCA. Recently, some scholars have tried to integrate ABM and LCA to simulate environmental impacts. However, most studies have been conducted in the agricultural field. Ding and Achten (2022) [28] used ABM to model the dynamic inventory associated with land-use decisions and conducted environmental impacts assessment following LCA framework. Marvuglia et al., (2017) [29] integrated ABM and LCA to simulate future crop patterns based on farmer–environment interactions and quantified related environmental impacts. These studies have verified the feasibility and enhancement of integrating ABM and LCA. However, most of these studies focused on the quantitative evaluation process, with only a few involving optimization modeling and decision-making [30]. Besides, previous studies have largely been conducted in a static context, failing to account for potential temporal variations and dynamic factors.

3 Material and methods

3.1 ABM–DLCA framework

This study integrates ABM and DLCA to establish a dynamic environmental impacts assessment and optimization model for buildings. The university dormitory buildings located in Nanjing, China, for graduate students are chosen as the evaluation object in this study. As critical components of higher education infrastructure in China, university dormitories are characterized by large floor areas, high occupancy, and significant energy consumption, making them a significant target for environmental management and optimization.

Following the LCA paradigm and adopting ABM to capture the interactions between dynamic factors, this study designed an integrated ABM–DLCA framework with three simulated modules, considering the dormitory management characteristics (as shown in Fig. 1). In the first module, the climate, dormitory, and students, representing three typical dynamic factors, are modeled as autonomous agents in the ABM platform. Their behaviors and dynamic interactions are simulated to calculate the consequential dynamic energy consumption. The second module analyzes the dynamic elements in DLCA and incorporates them into the ABM model to quantify temporal impacts. The third module introduces an administrator agent to conduct management strategies. The administrator agent adjusts the behaviors of agents in module 1 based on the LCA results fed back from module 2, enabling real-time adaptation of management strategies. This continuous exchange of data and information establishes a closed feedback loop, embedding optimization within the environmental impact assessment process.

Figure 1 ABM–DLCA model

This study couples ABM with DLCA to realize enhancement in the following three aspects. First, ABM can simulate interactions between dynamic factors based on predefined rules, thereby capturing their combined effects on the overall system. Second, ABM simulates interaction behaviors between agents based on real-world situations, providing consumption data with higher representativeness for impact assessment. Third, optimization strategies are proactively incorporated into the assessment framework through feedback. The LCA evaluation results can be fed through an ABM loop, allowing decision-makers to explore the consequences of various interventions and optimize sustainability strategies by adjusting agent behaviors.

3.2 Module 1: Energy simulation

3.2.1 Agents analysis

This module simulates the dormitory's dynamic energy consumption by modeling the interactions between three agents: climate, dormitory, and student agents. The climate agent represents external environmental conditions, which directly affect the indoor energy usage. The dormitory agent encompasses the physical characteristics of dormitory buildings and energy-consuming devices, such as air conditioning (AC), lighting, and computers. The student agent models the behaviors and activities of dormitory occupants, including their presence usage patterns of electrical devices, and green consciousness. The simulation primarily focuses on electrical energy consumption due to its significant role in dormitory energy use.

Each agent type has specific attributes, states, and behavior rules, with details explained in the corresponding sections. To develop the model accurately, this study conducted a comprehensive data collection process, including a questionnaire survey to understand student behavior, field research to observe energy usage patterns,

and a literature review to gather data. This module adopts temporal parameters, variables, and functions to conduct dynamic energy simulation.

3.2.2 Climate agent

External environmental conditions, such as temperature, significantly influence indoor environment and students' usage of heating and cooling energy devices. Hourly temperature data is adopted for this agent in the model to temporally simulate students' energy use behaviors, and temperature is set as the main attribute of climate agent. The hourly temperature data are obtained from the ERA5 dataset published by the European Center for Medium-Range Weather Forecasts. This dataset can provide global hourly temperatures and has been widely used in current studies [31].

3.2.3 Dormitory room agent

The main function of the dormitory room agent is to provide living space for students, where students' operation of appliances directly contributes to the environmental impacts of dormitory buildings. As shown in Table 1, the attributes of the dormitory room agent mainly include the room number, the number of different devices and their operating power. Three major types of energy-consuming devices are involved (i.e. air conditioners, computers, and lights) for they account for approximately 85%-90% of the total energy consumption within dormitories [32]. Given that Nanjing is located in the non-central heating region of China, winter heating in graduate dormitories primarily relies on air-conditioning. The use of other heating devices is generally not permitted. Therefore, their energy consumption is not considered in this study. Energy consumption of these appliances is closely linked to their usage patterns and operating power. The use of personal computers is directly determined by individual students. While for shared equipment like air conditioners and lights, students exhibit variations in their preferred usage patterns. To avoid potential conflict, the usage patterns of shared devices is determined by predefined rules. For air conditioners, they will be turned on when the indoor temperature falls out the comfort range and turned off when the indoor temperature is comfortable. For lights, they are kept off during sleeping hours. During wake hours, they are turned on when the dormitory is occupied and turned off when it is unoccupied.

Table 1
Attributes of dormitory room agent

No.	Attribute	Description	Data Source
1	roomNo	Room Number	Field survey and Questionnaire
2	roomSize	Room Capacity	
3	roomACNumber	Number of Air Conditioners	
4	roomLightNumber	Number of Lighting	
5	roomACPower	AC Power	
6	roomACSetCoolTem	AC Cooling Temperature Setting	
7	roomACSetHotTem	AC Heating Temperature Setting	
8	roomLightPower	Lighting Fixture Power Consumption	
9	roomComputerRunPower	Computer operating Power	
10	roomComputerStandbyPower	Computer Standby Power	
11	agingCoefficient	the degree of energy performance degradation caused by aging	

As far as the parameter data, the occupancy status of dormitories is inferred from students' daily schedules, which will be introduced in Section 3.2.4. The indoor comfortable temperature ranges and air conditioner setpoints can be obtained from a questionnaire. The operating powers of different devices can be obtained from field survey and relevant standards. It should be noted that appliances age with continued service, resulting in increased power demand. Therefore, the aging coefficient is introduced to characterize the dynamic variation in appliance energy consumption, its value is set to increase linearly by 3% annually.

Table 1 Attributes of dormitory room agent

3.2.4 Student agent

The student agent significantly influences the dormitory's energy consumption through their presence and behaviors within the dormitory. The attributes of student agent are set using data from a comprehensive questionnaire, which comprises four parts: basic information, daily schedules, energy-use behaviors, and green consciousness, as shown in Table 2. Details of the full questionnaire are provided in Supplementary Material.

Table 2
Attributes of student agent

No.	Attribute	Description	Data Source
1	grade	Including first-year, second-year and third year	Questionnaire (Question 1)
2	getUpTime	Time of getting up	Questionnaire (Questions 2–15)
3	prepareTime	Time taken to get ready after waking up	
4	noonBreakProbability	Probability of returning to dorm for a nap	
5	noonBreakDuration	Duration of a noon nap in dormitory	
6	returnTime	Time of returning to the dormitory and not going out again	
7	bedTime	Time of going to bed	
8	weekdayMorningStayProbability	Probability of staying in dorm in the morning on weekdays	
9	weekdayAfternoonStayProbability	Probability of staying in dorm in the afternoon on weekdays	
10	weekdayNightStayProbability	Probability of staying in dorm at night on weekdays	
11	weekdayMorningStayProbability	Probability of staying in dorm in the morning at weekends	
12	weekdayAfternoonStayProbability	Probability of staying in dorm in the afternoon at weekends	Questionnaire (Questions 16–31)
13	weekdayNightStayProbability	Probability of staying in dorm at night at weekends	
14	winterHolidayResidenceRatio	Proportion of time spent in dorm during winter vacation	
15	summerHolidayResidenceRatio	Proportion of time spent in dorm during summer vacation	
16	computerUseProbability	Probability of using a computer in dorm	
17	computerType	Including laptop computer and desktop computer	
18	weekdayComputerUseTime	The duration of computer use on weekdays in a day	
19	weekendComputerUseTime	The duration of computer use at weekends in a day	
20	hotToleranceTem	Temperature tolerance to heat	
21	coolToleranceTem	Temperature tolerance to cold	
22	greenConsciousness	Including high, medium and low levels	Questionnaire (Question 32)

No.	Attribute	Description	Data Source
23	transitionProportion	The transition proportion from low to medium level follows uniform (0,0.2), whereas the transition proportion from medium to high follows uniform(0,0.3)	Literature

The presence of students is modeled through daily schedules by defining the probabilities of typical activities at given times based on academic calendar. The probabilities of students staying in the dormitory during different time periods of a day, the duration of naps, the wake-up time and bedtime are set as attributes of the student agent. Students' daily schedules differ across weekdays, weekends, and holidays. During summer and winter vacations, most students return home, which reduces the energy consumption of dormitories. Additionally, graduate students in different grades have varying class schedules. This alters the periods they stay in the dormitory and, consequently, affects the operating hours of appliances. Therefore, this study set heterogeneous daily schedules for student agents from different grades.

Students' behavioral attributes include thermal tolerance, computer-use habits, and level of green consciousness. Thermal tolerance reflects students' preference of indoor thermal comfort and directly influences the activation threshold of air conditioners. Computer usage habits are mainly measured by the daily usage duration on weekdays and weekends. Green consciousness measures students' likelihood of adopting energy-saving behaviors [30]. It influences students' preference of temperature setting of air conditioners and computer-use habits. The green consciousness of students is categorized into three levels (i.e. high, medium, and low) according to the questionnaire survey. Noted that students' behaviors are influenced by their peers, which may lead them to adopt similar practices. Consequently, students' green consciousness level is modeled as a dynamic parameter that transitions to higher levels at a defined transition rate, as shown in Table 2.

Table 2 Attributes of student agent

3.2.5 Interactions and energy calculations

The simulation of Module 1 uses an hourly time step and outputs the annual building-level energy consumption. The calculation equations and related parameters are summarized in Table 3. First, the model determines students' preferences on air conditioner setpoints and computer use patterns based on their green consciousness level. Then, the model reads temperature data from the climate agent and daily schedule from the student agent to determine the operation states of devices. The cumulative operating hours of devices are calculated based on Eq. 1–2. Next, the model calculates the energy consumption for each dormitory room, as shown in Eq. 3–4. Finally, building-level energy consumption is aggregated, as indicated in Eq. 5.

Table 3
Energy calculation equations and parameters description

No.	Equations	Descriptions
1	$TR_{i,n}(t) = \sum_k T_{i,k,n}(t)$	$TR_{i,n}(t)$ represents total running time of appliance i in room n on day t; $T_{i,k,n}$ represents the running time of the k-th appliance i; k indicates air conditioner and lighting equipment.
2	$TC_{s,n}(t) = \sum_j T_{s,j,n}(t)$	$TC_{s,n}(t)$ represents the total running time of computer in state s in room n on day t; $T_{s,j,n}(t)$ represents the running time of the j-th computer; and s includes operation and standby state.
3	$\alpha_{t,y} = 0.03 \times (t_y - 2018)$	$\alpha_{t,y}$ represents the aging coefficient in year t_y.

No.	Equations	Descriptions
4	$ER_n(t) = \sum_i TR_{i,n}(t) \times P_i \times (1 + \alpha_{t,y}) + \sum_s TC_{s,n}(t) \times PC_s \times (1 + \alpha_{t,y})$	$ER_n(t)$ represents the energy consumption of room n on day t; P_i represents the operating power of appliance i; and PC_s represents the power of computer in state s.
5	$EB(t) = \sum_n ER_n(t)$	$EB(t)$ represents the total energy consumption of the dormitory building on day t.

Table 3 Energy calculation equations and parameters description

3.3 Module 2: Dynamic environmental impact assessment

DLCA incorporates time-dependent variations into the assessment by following the LCA framework and paradigm. It typically comprises four essential types of assessment elements: dynamic consumption data, dynamic background inventory datasets, characterization factors, and dynamic weighting factors [8]. To realize the automated assessment of environmental impacts, three agents associated with the dynamic assessment elements are established: dynamic background inventory agent, characterization factor agent, and dynamic weighting factor agent. Important life cycle assessment parameters are set as attributes of these agents, as shown in Table 4.

Table 4
Attributes of agents in module 2

Agent	Attributes	Data source
Dynamic background inventory	BackgroundInventoryData	Literature
Characterization factor	CharacterizationFactor	Literature
Dynamic weighting factor	WeightingFactor	Literature

Table 4 Attributes of agents in module 2

Module 1 provides dynamic energy consumption data of dormitory buildings. Dynamic background inventory agent converts dynamic consumption into input and output flows. Considering that electricity is the main source of energy consumption in dormitory buildings, this study adopts dynamic background inventory of electricity from the literature [22].

The characterization factor agent quantifies the relative contribution of input and output inventories to different environmental impact categories. Different types of pollutants can cause the same type of environmental impact. For example, CO₂ and CH₄ can both lead to global warming. Therefore, characterization factors are employed to aggregate the environmental impacts caused by different pollutants into the same category. This study focuses on four common environmental impact categories: global warming, acidification, eutrophication, and airborne suspended particles. A characterization factor agent is established for each environmental impact category, and the corresponding characterization factors are set as attributes of each agent.

Dynamic weighting factor agent converts different types of environmental impacts with varying units into a single value, reflecting public tolerance to different environmental issues. The dynamic weighting system developed by Su et al., (2019) [12] based on the distance-to-target approach is adopted to assign values to the attribute of this agent.

3.4 Module 3: Management and optimization

In traditional LCA studies, environmental impacts are typically presented as post-analysis results, making it difficult to further guide the selection and adjustment of management strategies. To address this limitation, this module introduces an administrator agent to establish a bidirectional feedback loop between decision variables and environmental impact results, thereby embedding the optimization process into the LCA framework as an iterative decision-making mechanism. Considering that climate is difficult to be altered artificially, this study focuses on the other two types of agents (i.e. dormitories and students) in module 1. It proposes and evaluates two targeted optimization strategies: students' green consciousness improvement and dormitory allocation optimization. Details of these strategies are introduced below. In this module, the administrator agent evaluates the environmental impacts annually after the implementation of these optimization strategies, and then conducts adjustment based on their impact-reduction effect. The attributes of the administrator agent are shown in Table 5.

Table 5
key attributes of the administrator agent

No.	Attribute	Description
1	ActivityImpactCoefficient	Degree of improvement in students' green consciousness level for each energy conservation activity
2	AllocationRatio	Allocation ratio for different dormitory types

Table 5 key attributes of the administrator agent

3.4.1 Green consciousness improvement strategy

Students' green consciousness level affects their energy-use behaviors, thereby influencing the environmental impacts of dormitory buildings. In addition to the peer influence mentioned before, existing studies have demonstrated that university administrations can proactively improve students' green consciousness through activities such as cultivating an energy conservation culture, organizing green competitions, and providing environmental protection education [33]. In this strategy, the administrator agent organizes a series of energy-saving activities, such as lectures and competitions, to improve students' green consciousness, incentivizing the adoption of energy-saving behaviors. The impact coefficients of these activities are specified as attributes of the administrator agent to quantify the changes in students' green consciousness, as shown in Table 5.

The implementation process of this strategy is as follows. First, the administrator agent determines the types and frequencies of energy-saving activities for the current academic year. Students' green consciousness is dynamically updated accordingly. Then, the model calculates and compares the annual environmental impacts before and after the implementation of this optimization strategy. If a reduction in impacts is observed, the strategy is retained for the subsequent academic year.

3.4.2 Dormitory allocation strategy

The environmental impact of dormitory buildings can be significantly influenced by the dormitory allocation strategy. Energy consumption of dormitories with same-grade students is usually lower than that of mixed-grade dormitories. This is because same-grade students often share similar schedules, study habits, and social activities, leading to more consistent patterns of energy use. For example, first-year graduate students typically have more fixed coursework and daytime presence, while upper-year graduate students might have more flexible and fragmented schedules due to internships or off-campus activities. These differences in daily schedules can lead to more diverse energy-use behaviors in mixed-grade dormitories, extending the operating hours of shared equipment. In addition, upper-year students often face greater research pressure, which may lead to longer computer use. Therefore, the mixed-grade dormitories usually exhibit more higher overall environmental impacts compared to same-grade dormitories [34]. Although allocating dormitories by grade is more environmentally friendly, mixed-grade housing is often unavoidable due to various practical reasons. Transitioning from mixed to same-grade housing requires significant time and effort. This section focuses on evaluating the environmental benefits of such management measures.

The dormitory allocation strategy is implemented by the administrator agent. First, the administrator agent calculates the annual per-student environmental impacts for each type of dormitory to identify those with the lowest and highest levels. Next, the administrator agent reallocates dormitories to increase the proportion of

low-impact dormitory type. Students then move to new dormitories. This process is repeated annually at the end of academic year.

3.5 Case Study

The proposed model is applied to graduate dormitory buildings located on a university campus in Nanjing, China (as shown in Fig. 2). The dormitory area comprised 10 buildings, containing 125 rooms and 500 students. Each room has a shared air conditioner and two electric lights. The graduate students are enrolled for three years; therefore, the study period covers three consecutive academic years (September 2018 to September 2021), denoted as Periods 1–3.

Figure 2 Exterior view and geometric representation of the dormitory building: (a) Exterior photograph; (b) front view of the building model; (c) side view; (d) top view; (e) spatial layout of the ten buildings

Participants were selected through stratified random sampling based dormitory buildings and grade levels. A total of 201 questionnaires were retrieved, of which 178 were valid, covering students from all dormitory buildings and grade levels. Students' daily schedule, energy-use behaviors, and green consciousness levels were collected, with detailed data provided in Supplementary Material (Table S1–S3). Given the lack of standardized heating and cooling schedules in Nanjing, the questionnaires included relevant questions to estimate the actual operating periods of dormitory air conditioners. The results indicated a cooling period from May 20 to August 31 and a heating period from November 21 to February 28. According to the university's academic calendar, the academic year begins on September 1, with winter vacation from January 1 to February 4, and summer vacation from July 1 to August 31. A field survey was conducted to obtain the number of dormitories, the quantify and operating power of appliances, and the initial dormitory allocation. Detailed data are presented in Supplementary Material (Table S4). At the beginning of research period (i.e. 2018), all dormitories were mixed-occupancy. Parameter values for the dynamic background inventory agent, characterization factor agent, and dynamic weighting factor agent were obtained from the literature.

For the dynamic parameters in each module (Table 6), the following value assignment strategies were adopted in the case study. The dynamic parameters involved in Module 1 include temperature, appliance aging coefficient, and students' green consciousness level. Their dynamic changes follow the rules introduced in Section 3.2. In Module 2, the dynamic background inventory and dynamic weighting factors adopt year-specific values corresponding to the simulation year. In Module 3, the value of students' green consciousness level and dormitory allocation proportion changes through two optimization strategies. The green consciousness improvement strategy, implemented through publicity and education, is assumed to increase the green consciousness level of 26% of students each year [35]. The dormitory allocation strategy aims to convert all mixed-grade dormitories into same-grade dormitories at a steady annual rate.

Table 6
Dynamic parameters in each module

Module	Agent	Dynamic parameters
Module 1	Climate	Temperature
	dormitory	Aging Coefficient
	student	Green Consciousness
Module 2	Dynamic background inventory	Background Inventory Data
	Dynamic weighting factor	Weighting Factor
Module 3	Administrator	Dormitory allocation proportion

Table 6 Dynamic parameters in each module

4 Results and discussion

4.1 Simulation results

The simulation was repeated 20 times in AnyLogic, and the average values were selected as the final simulation results. To validate the model, actual monthly dormitory electricity consumption data in Period I was obtained from the university's published records. Monthly deviation between the simulated results and the actual data was calculated, as shown in Fig. 3. The value of R^2 between the simulated results and the actual values reached 0.95, with a mean percentage difference of 5.6% and a maximum percentage difference below 12%, indicating the good fitness of the model.

Figure 3 Comparison of simulated and actual results and monthly environmental impacts in Period I

The temporal variations of the environmental impacts in Period I are also illustrated in Fig. 3. The environmental impacts of the case buildings reach its peak in December (5.12×10^4) and June (4.08×10^4). During these periods, students frequently utilize air conditioner for heating and cooling to maintain comfortable indoor thermal environment, leading to substantial energy consumption and sharp increase in environmental impacts. In contrast, the environmental impacts reach its troughs in October, March, and April. The environmental impact values during these months remains lower than 6000 units. The mild outdoor temperatures significantly reduced the frequency of air conditioner usage, thereby reducing the environmental impacts.

A notable phenomenon is the significant decrease in environmental impacts observed in January and July. According to the academic calendar, these months correspond to the winter and summer vacations, when reduced dormitory occupancy effectively offset the potential heating and cooling demands caused by extreme outdoor temperatures. Consequently, although January and July are typically peak periods for cooling and heating demand, the environmental impacts generated by the case buildings are still low. Besides, a rebound in environmental impacts appears in February and August. owing to some students returning to campus before the end of the holiday.

The results in Fig. 3 demonstrate that the environmental impacts of the building are not driven by a single dynamic factor, but are influenced by the combined and time-dependent interactions between different factors.

The influence of changes in students’ schedules on the energy consumption of case buildings in summer provides robust evidence for this. Considering the dynamic factors of single factors not only leads to significant errors in the assessment results, but also fails to capture the correct temporal changes of environmental impacts.

4.2 Spatiotemporal annual impacts analysis under different optimization strategy

The green consciousness improvement and dormitory allocation strategies proposed in Section 3.4 were implemented to evaluate their optimization effects over the operational cycle. Improvements in students’ green consciousness are reflected through the “greenConsciousness” parameter, while the changes in dormitory allocation are captured by the “allocationRatio” parameter. The dynamic values of these two parameters are shown in Table 7.

Table 7
Parameter values under optimization scenarios

Management strategy	Parameter	Values for Period Ⅹ	Values for Period Ⅹ	Values for Period Ⅹ
Green consciousness improvement	Students’ green consciousness level	Percentages: High level: 42%	Percentages: High level: 56%	Percentages: High level: 68%
		Medium: 43%	Medium: 35%	Medium: 25%
		Low: 15%	Low: 9%	Low: 7%
Dormitory allocation	Proportion of mixed-grade dormitories	100%	50%	0%

Table 7 Parameter values under optimization scenarios

The specific environmental impacts of each building after the implementation of the optimization strategy are shown in Fig. 4. According to Fig. 4 (a), when no optimization strategy was applied, the environmental impacts of the dormitories increased gradually over the operational cycle. From 2018 to 2020, the annual environmental impact increased by 6.71%. This increase is mainly driven by the degradation of energy-consuming devices over time, which raises operating power. As a result, more energy was required to maintain the same thermal comfort, leading to higher environmental impacts. From the spatial perspective, the variation in environmental impacts between different dormitories within the same year are relatively limited.

As shown in Fig. 4 (b) and (c), compared to the no-optimization scenario, both optimization strategies reduced the environmental impacts compared to the no-optimization scenario. When only the green consciousness improvement strategy was implemented, the cumulative environmental impact across the operational cycle decreased by 2.69%. The reductions were relatively uniform across different dormitories, as this strategy encourages energy-saving behaviors without exhibiting significant spatial heterogeneity.

In contrast, the implementation of the dormitory allocation strategy produced more pronounced spatiotemporal changes. The aggregate annual environmental impacts declined gradually over time, and by 2020, the cumulative environmental impacts over 2018–2020 had decreased by 5.15% compared to the no-optimization scenario. Spatially, the environmental impacts of Buildings 7, 8 and 9 declined by more than 30%, while changes in other

dormitories were limited. Although the dormitory allocation strategy did not reduce the environmental impacts of every building, it still effectively narrowed the differences in students’ daily schedules, concentrated device-use periods, and thereby achieved a substantial reduction in cumulative environmental impacts.

Figure 4 Environmental impacts of the case-study buildings under different optimization scenarios:(a) no-optimization;(b) green awareness improvement;(c) dormitory allocation;(d) combined implementation of both strategies; (e) cumulative environmental impacts of all dormitories over the study period

4.3 Interactive analyses of dynamic factors

To evaluate the interactive effects of dynamic factors on environmental impacts, this section evaluates the isolated impact of individual dynamic parameter as well as their combined effects under interaction. These results are then compared with a static scenario. Specifically, temperature, aging coefficient, and student green consciousness were selected from the three interactive agents (i.e., climate, dormitory and student) to represent dynamic changes in external environment, energy-consuming devices, and occupant behavior, respectively. As shown in Table 8, in the single-factor dynamic scenarios, only the targeted factor adopts dynamic values, while all other parameters remain static. In the multi-factor analysis, all selected factors vary dynamically, and in the static scenario, all the parameters remain static.

Table 8
Parameter values under dynamic and static scenarios

Parameters	Dynamic value	Static value
temperature	Using year-specific hourly temperature for 2018–2020	Using hourly temperatures in 2018 for all three years
Aging coefficient	Increasing linearly by 3% annually from 2018–2020	Using aging coefficient in 2018 for all three years
Students’ green consciousness	Influenced by both peer interactions and participation in university’s education activities	Maintained at the 2018 level

Table 8 Parameter values under dynamic and static scenarios

Table 9 summarized the cumulative environmental impacts of each scenario over the study period. Results for dynamic (both single-factor and multi-factor) and static scenarios and the multi-factor scenario show significant differences compared to the static scenario. When only considering the dynamics of climate or appliance power, the environmental impacts increase compared to the static scenario. On the one hand, extreme global weather trends lead to increased heating and cooling loads under the dynamic climate scenario. On the other hand, the increasing appliance operation power caused by degradation results in higher energy demand to satisfy equivalent thermal comfort. In contrast, dynamic changes in green consciousness significantly reduce environmental impacts. Interactions among students encourage the adoption of energy-saving behaviors, thereby decreasing appliance energy consumption and associated environmental burdens. Notably, the difference between multi-factor and static scenarios does not simply equal to the simple sum of differences from the single-factor scenarios. This demonstrates the non-linear interactions between dynamic factors and highlights their combined effect on the assessment results.

Table 9
Environmental impacts under dynamic and static scenarios

Static scenario	Environmental impacts	Difference from the static scenario
	5.99×10^6	/
Dynamic weather	6.10×10^6	1.09×10^5
Dynamic appliance power	6.22×10^6	2.26×10^5
Dynamic green consciousness	5.81×10^6	-1.82×10^5
Multi-factor dynamic	6.10×10^6	-1.08×10^5

Differences in assessment results between single dynamic factor scenarios and the static scenario demonstrate the necessity of considering dynamic factors in the assessment of building environmental impact because they do affect the assessment results. The multi-factor analysis further emphasizes the value of a holistic and integrative perspective, which enables a more objective and accurate representation of changes in building environmental impact. It helps to avoid overly optimistic or pessimistic biases that may arise from single-factor analysis.

Table 9 Environmental impacts under dynamic and static scenarios

4.4 Influence of initial status on optimization effects

The final effect of optimization strategies will be significantly influenced by initial status [36]. When the system is in a good initial status, the implementation of optimization strategies may not bring obvious enhancement, giving rise to the misunderstanding that the optimization strategies are ineffective. In contrast, when the system is in a relatively bad initial status, the effect of optimization strategies may be overestimated, as poorer conditions are inherently easier to improve. In order to assess the actual value of the proposed optimization strategies, this section conducted scenario analysis to investigate the effectiveness of simultaneously implementing green consciousness improvement and dormitory allocation optimization strategies when the initial conditions varied.

4.4.1 Initial green consciousness optimization

Three scenarios with different initial levels of green consciousness were set: baseline, medium and high. In the baseline scenario, students' actual green consciousness level obtained from questionnaire in the case study were adopted, with 42%, 43%, and 15% of students having high, medium, and low level of green consciousness, respectively. In the medium green consciousness scenario, the proportion of student with medium and high levels of green consciousness are both 50%. In the high green consciousness scenario, all students are assumed to be at the high level.

Figure 5 presents the optimization effects of these two proposed strategies when students' initial green conscious varies. Some finding can be drawn from the results.

First, regardless of students' initial green consciousness, the cumulative environmental impacts of the dormitories consistently decrease during the operation cycle under the effect of both green consciousness level improvement and dormitory allocation strategies. By 2020, the annual environmental impacts in the baseline,

medium and high green consciousness scenarios decreased by 1.17×10^5 , 7.73×10^4 , and 7.16×10^4 units, respectively, compared to 2018. Even in the high green consciousness scenario, the environmental impacts can be further reduced through allocation strategies. This highlights that effective environmental management depends on both individual behavior and the coordinated implementation of organization measures. Therefore, even in ideal scenarios where occupants exhibit high green consciousness, it is still essential to maintain a strong focus on environmental management. Second, the higher the initial level of students' green consciousness, the lower the annual and cumulative environmental impacts generated by the dormitories. Compared to the baseline scenario, the cumulative environmental impacts under the medium and high green consciousness scenarios decreased by 3.97% and 19.73%, respectively. This finding emphasizes the value of initiating energy-saving education at an early stage. Cultivating students' energy saving awareness in their early years fosters the internalization of green consciousness into long-term, stable behavioral habits, generating lasting positive environmental benefits throughout their university life and future daily life.

Figure 5 Environmental impacts under different initial green consciousness scenarios

4.4.2 Initial dormitory allocation strategy optimization

Figure 6 illustrates the effect of initial dormitory allocation strategies on the dormitory's environmental impact. The scenarios show that the initial proportion of same-grade dormitory students are 0% (baseline scenario), 20%, 50%, 75%, and 100%. All scenarios aim to steadily decrease the proportion of mixed-grade dormitories to 0% throughout the operation stage. Although the initial percentage of same-grade dormitory students varies under different scenarios, the implementation of optimization strategies still leads to a gradual reduction in environmental impacts in all scenarios. By 2020, the proportion of same-grade dormitory students and their green consciousness have reached the same level owing to the implementation of optimization strategies. Consequently, the environmental impacts were identical across scenarios in that year. Similar to the improvement of green consciousness, increasing the proportion of same-grade dormitory students reduces the environmental impacts generated by dormitories. Over the operation cycle, the cumulative environmental impacts differed significantly across scenarios. The difference in cumulative impact between the baseline and the 100% same-grade dormitory scenarios reaches 2.98×10^5 units. Therefore, assigning new students to the same dormitory at the beginning of the academic year, and thus avoiding mixed grade assignments, can minimize the environmental impacts generated during the operational cycle.

Figure 6 Environmental impacts under different initial dormitory allocation strategy optimization scenarios

4.5 ABM–LCA integration

This study integrated ABM and LCA to study the complex interactions between individual agents and their resulting environmental impacts. As illustrated in Fig. 7, existing ABM-LCA framework can be generally classified into three main types: an ABM feeding information to an LCA, an LCA feeding information to an ABM, and a coupling in which information flows in a loop between both models [37].

In the first type, ABM generates consumption data by simulating the behaviors and interactions of agents. These data are subsequently input into LCA tools as foreground inventory, with following evaluation steps performed within the LCA software. For example, Guo et al., (2025) [38] obtained the building materials and energy consumption data based on ABM and input them into LCA software to complete the assessment. In the second type, the environmental impact parameters of LCA, such as characterization factors and weighting factors, are

directly embedded within the ABM model. This enables the ABM model to conduct the assessment internally and output final results automatically. For instance, Su et al., (2025) [39] modeled characterization and weighting factors as individual agents in the ABM model, facilitating the automated evaluation of the environmental impacts of a campus. In the third type, utilized in this study, ABM and LCA exchange information dynamically in a continuous loop. In this study, ABM simulates the interactions between climate, dormitory, and student agents to provide a spatiotemporal dynamic foreground data flow for LCA. The environmental evaluation parameters embedded within the ABM model are then used to calculate the final assessment results. The assessment results are then fed back into the ABM to guide the implementation and adjustment of optimization strategies to minimize the environmental impacts. This deep coupling mechanism enhances the quality of the foreground data used in DLCA and reveals the optimization potential of different strategies, providing a robust reference for environmental management policies.

Figure 7 Three different integrations of ABM and LCA

The bidirectional deep coupling of ABM and LCA in this study has the following benefits. First, it reflects the impact on environmental systems in a more realistic way. Traditional LCA studies usually rely on statistical or local survey reports to obtain foreground data, which fails to capture the specific characteristics of the evaluated objects. In contrast, the ABM model can capture the heterogeneous behaviors of different occupants and simulate their actual energy-use patterns, providing consumption data that better reflect reality and enhancing the representativeness of assessment results. Second, it incorporates dynamic factors as agents into the ABM model, enabling the systematic consideration of their interactions. Current DLCA studies usually evaluate the impact of each dynamic factor independently and thus overlook their potential interactions, compromising the reliability of assessment results. Section 5.1 offers robust evidence to substantiate this argument. It demonstrates that the value of environmental impacts resulting from the interactions of multiple dynamic factors are not the simply the sum of individual effects. Third, it provides policymakers with a better understanding of the effectiveness of various interventions and policies for reducing environmental impacts. The integration of ABM and LCA enables both the quantification of optimization strategy effectiveness and whether agent-behavior adjustments are needed, forming a closed-loop of evaluation-feedback-resimulation. The closed-loop feedback mechanism can capture dynamic optimization effects over long-term implementation, helping managers to verify on-time attainment of intended optimization objectives. Further, the proposed model automated the assessment process. The complex LCA calculation equations are preconfigured with the ABM model, and the assessment results can be output automatically. However, traditional methods typically require manual data transfer between ABM model and LCA software. This not only leads conversion difficulties due to format incompatibility but also increases the risk of mismatches between consumption data and environmental parameters. In contrast, this automation avoids potential data converse issues between ABM and LCA and reduces manual efforts and errors, enhancing the efficiency of assessment.

5 Conclusion

This study proposed a deeply integrated ABM-DLCA model to systematically characterize the temporal interactions between dynamic factors and to integrate an optimization feedback mechanism into the assessment framework. ABM was employed to simulate the comprehensive interactions between three dynamic factors. Spatiotemporal dynamic consumption data were generated by assigning dynamic values to attribute parameters, such as temperature, operating power of devices, and students' green consciousness level. DLCA

was adopted to conduct the environmental impact assessment. Environmental assessment parameters, such as dynamic background inventories, characterization factors, and dynamic weighting factors were embedded into the ABM model to facilitate automated impact assessment. The assessment results were then fed back into the ABM model to guide the iterative optimization of agent behaviors and interactions. The proposed model was applied to dormitory buildings to demonstrate its applicability. The spatiotemporal environmental impacts of the case buildings during the operation cycle were calculated and the effect of different optimization strategies were quantified. Compared to existing studies, this study has two main contributions. First, it considers the interactions of multiple dynamic factors from a systematic perspective, reducing the risk of biased assessment results stemming from solely focusing on individual factors. Second, it enables the deep integration of ABM and LCA. The simulation results of the ABM model provide dynamic consumption data for LCA, while the LCA results are fed back into the ABM model to support agent adjustments. Based on the feedback results, managers can quantify the effectiveness of different optimization strategies and implement continuous adjustments. This closed-loop data flow transforms LCA from a retrospective evaluation tool into a proactive decision-support framework, thereby facilitating sustainable environmental management in the building sector.

Some key findings are drawn from this study:

1. The deep integration of ABM and DLCA not only significantly enhances the representativeness and efficiency of environmental impact assessments, but also enables the quantification of environmental benefits derived from optimization strategies, thereby extending the applicability of DLCA in environmental management.
2. It is essential to consider various dynamic factors and their interactions in a systematical way. Modeling multiple dynamic factors independently may lead to biased assessment results and undermine the reliability of the evaluation.
3. The optimization effects of management strategies are characterized by scenario dependency and temporal evolution. Incorporating optimization outcomes into the assessment through feedback mechanism helps reveal the dynamic effects of different management measures, facilitating timely adjustments by managers.

This study still has some limitations. Some assumptions and simplifications were inevitable in the ABM model due to the complexity of the real world. In addition, this study mainly focused on major energy-consuming devices, and small-scale appliances, such as hair dryers, were not fully considered. Future studies can further refine the interaction rules of the model to obtain results closer to real-world conditions.

Declarations

Declaration of competing interest

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

Author Contribution

S.S. contributed to conceptualization, supervision, funding acquisition, and writing the original draft. Q.G. contributed to methodology, formal analysis, writing the original draft, and writing, review and editing. Y.D.

contributed to methodology, software, formal analysis, writing the original draft, and writing, review and editing. A.H. contributed to data curation and writing the original draft. J.F. contributed to software and visualization. M.Z. contributed to visualization. All authors reviewed and approved the final manuscript.

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Data Availability

The datasets generated and/or analyzed during the current study are not publicly available because they contain case-study-specific building information and model inputs compiled for this study, but are available from the corresponding author on reasonable request.

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Figures

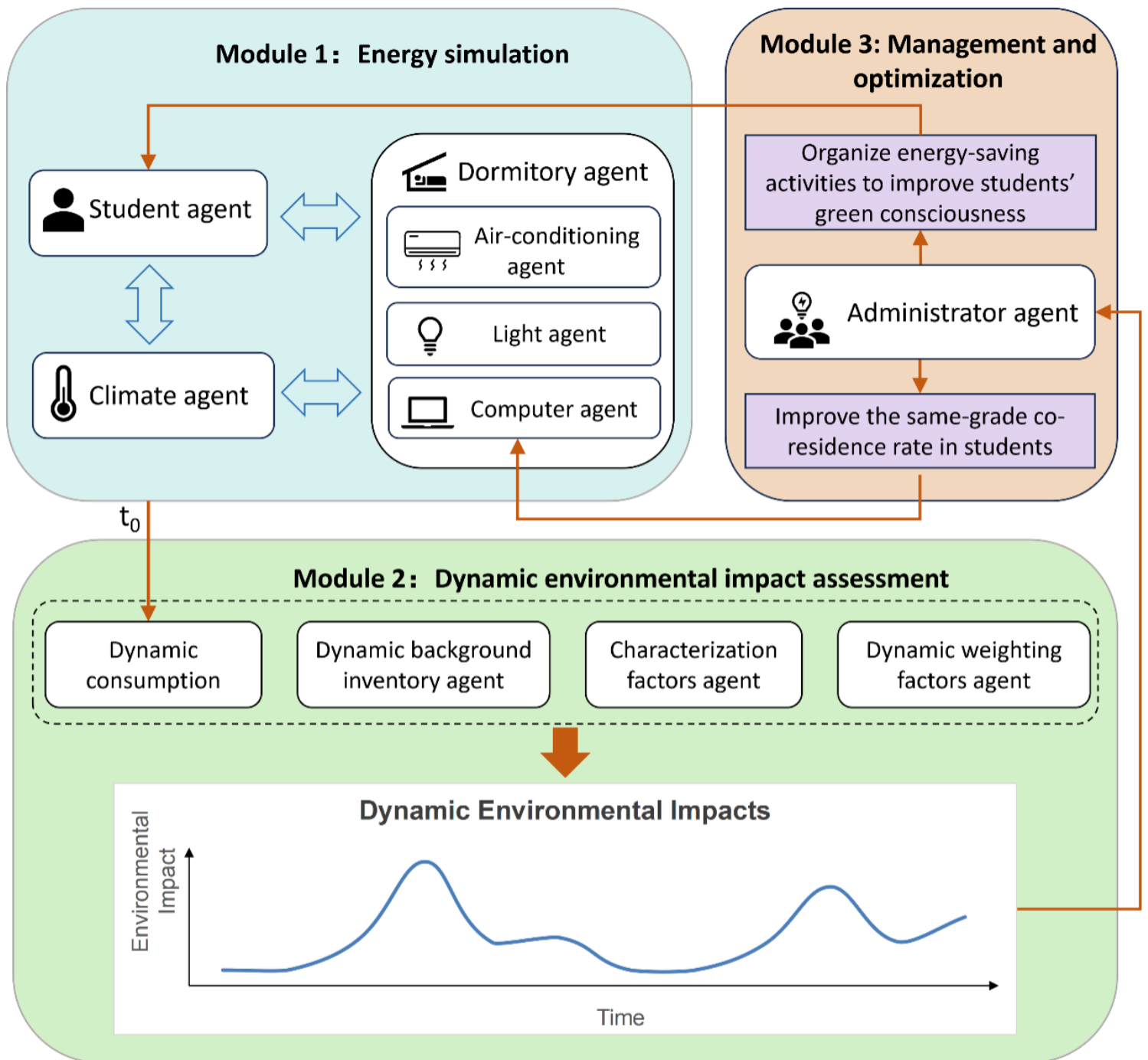
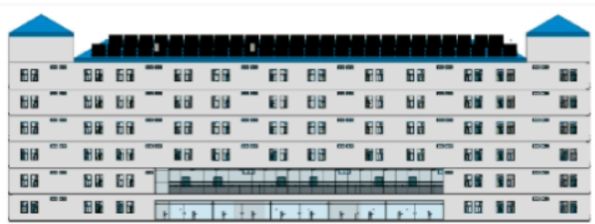


Figure 1

ABM-DLCA model



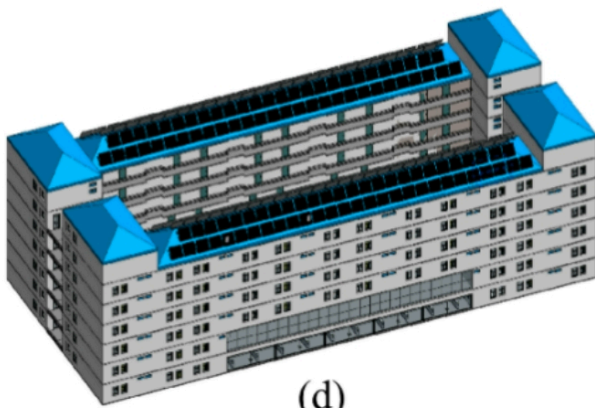
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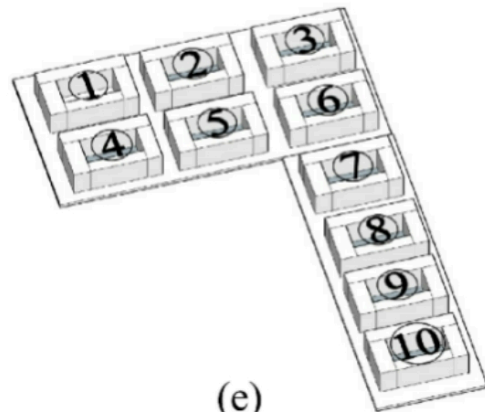
(b)



(c)



(d)



(e)

Figure 2

Exterior view and geometric representation of the dormitory building: (a) Exterior photograph; (b) front view of the building model; (c) side view; (d) top view; (e) spatial layout of the ten buildings

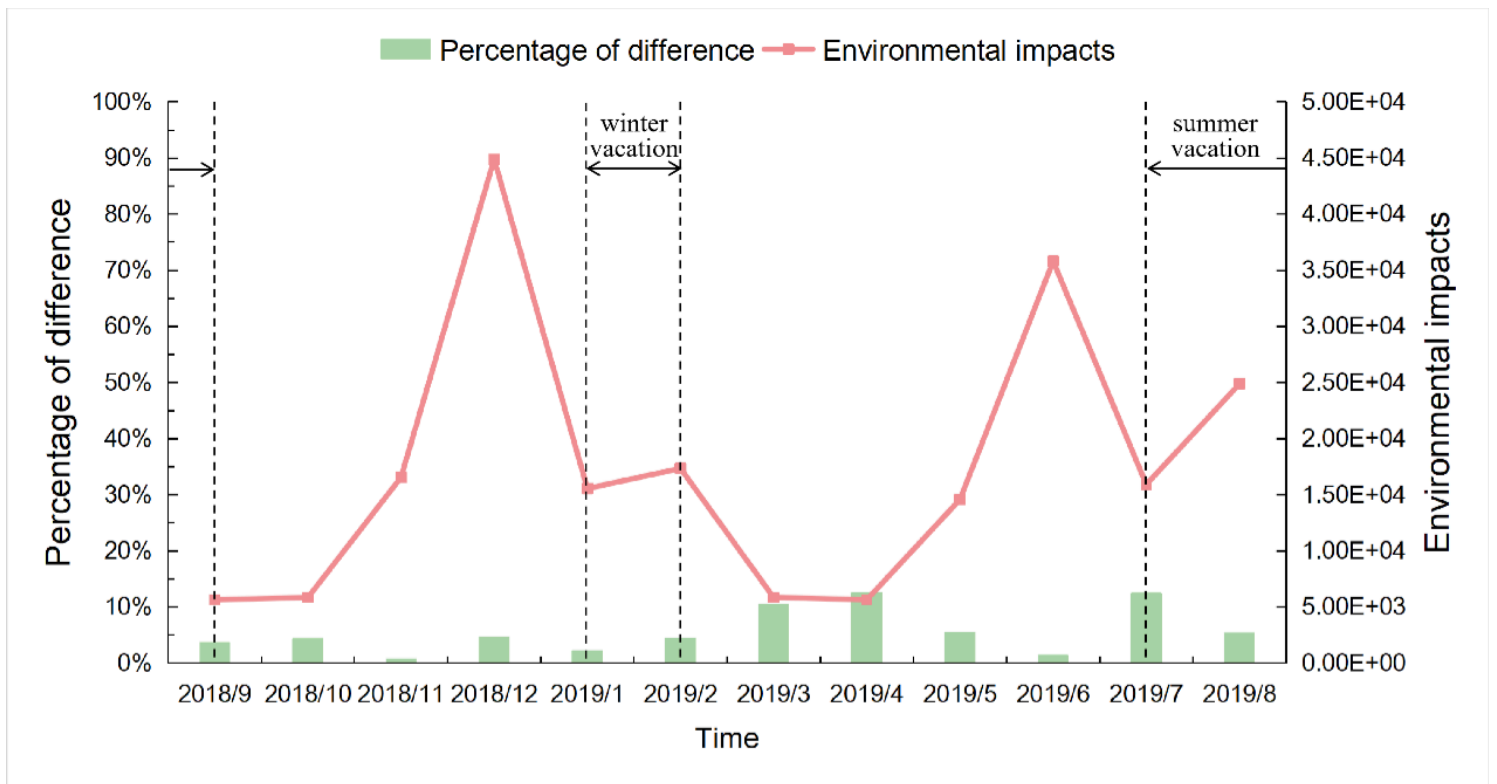


Figure 3

Comparison of simulated and actual results and monthly environmental impacts in Period I

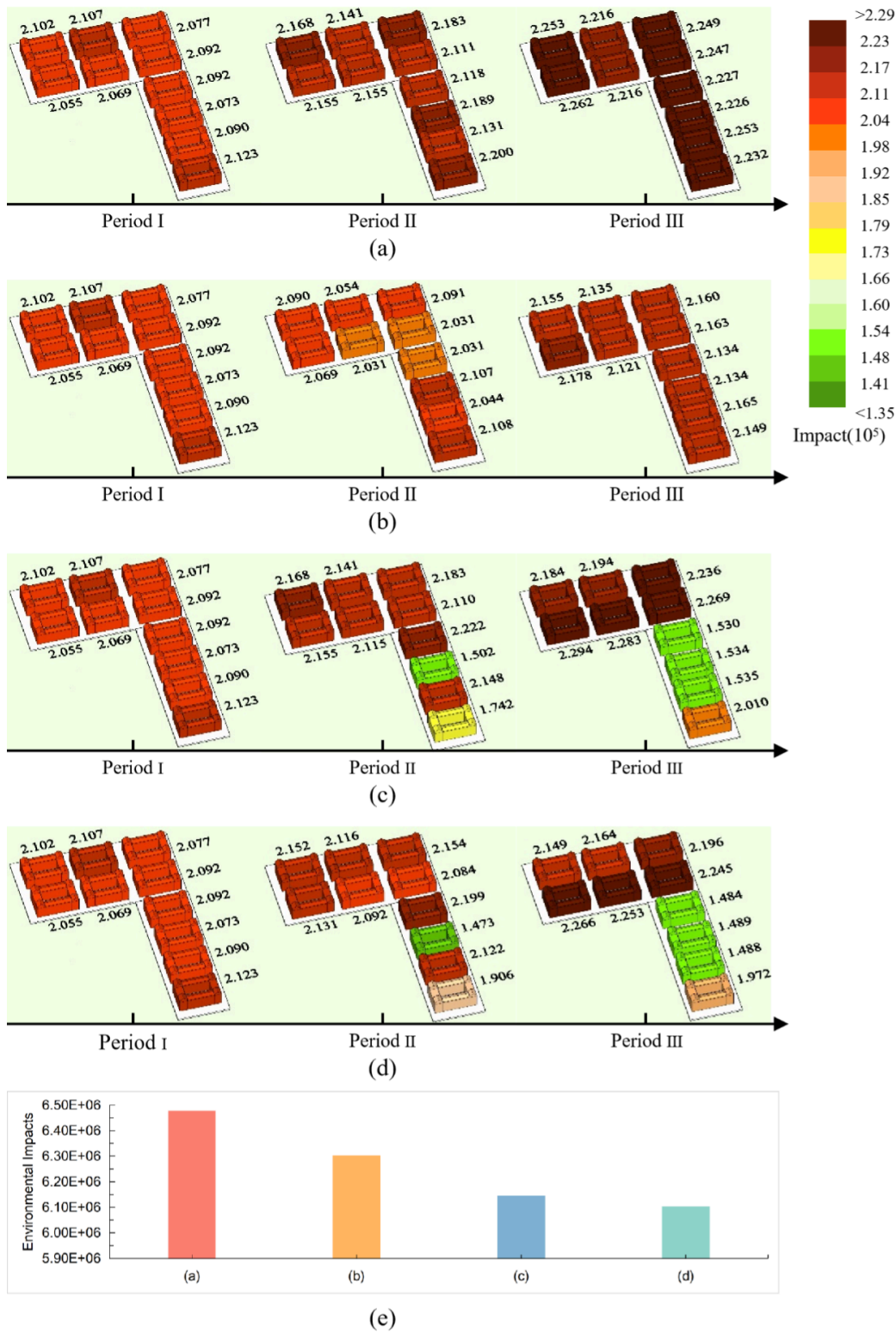


Figure 4

Environmental impacts of the case-study buildings under different optimization scenarios:(a) no-optimization;(b) green awareness improvement;(c) dormitory allocation;(d) combined implementation of both strategies; (e) cumulative environmental impacts of all dormitories over the study period

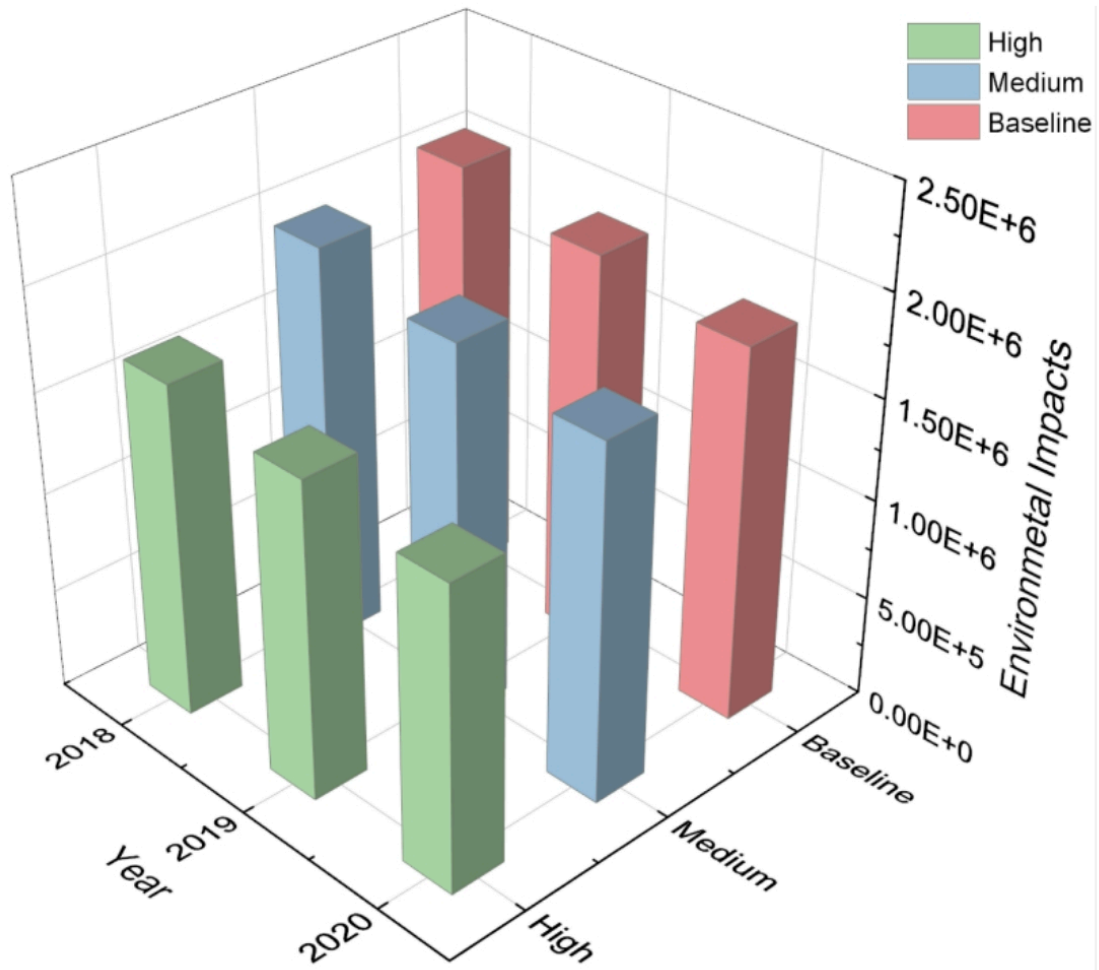


Figure 5

Environmental impacts under different initial green consciousness scenarios

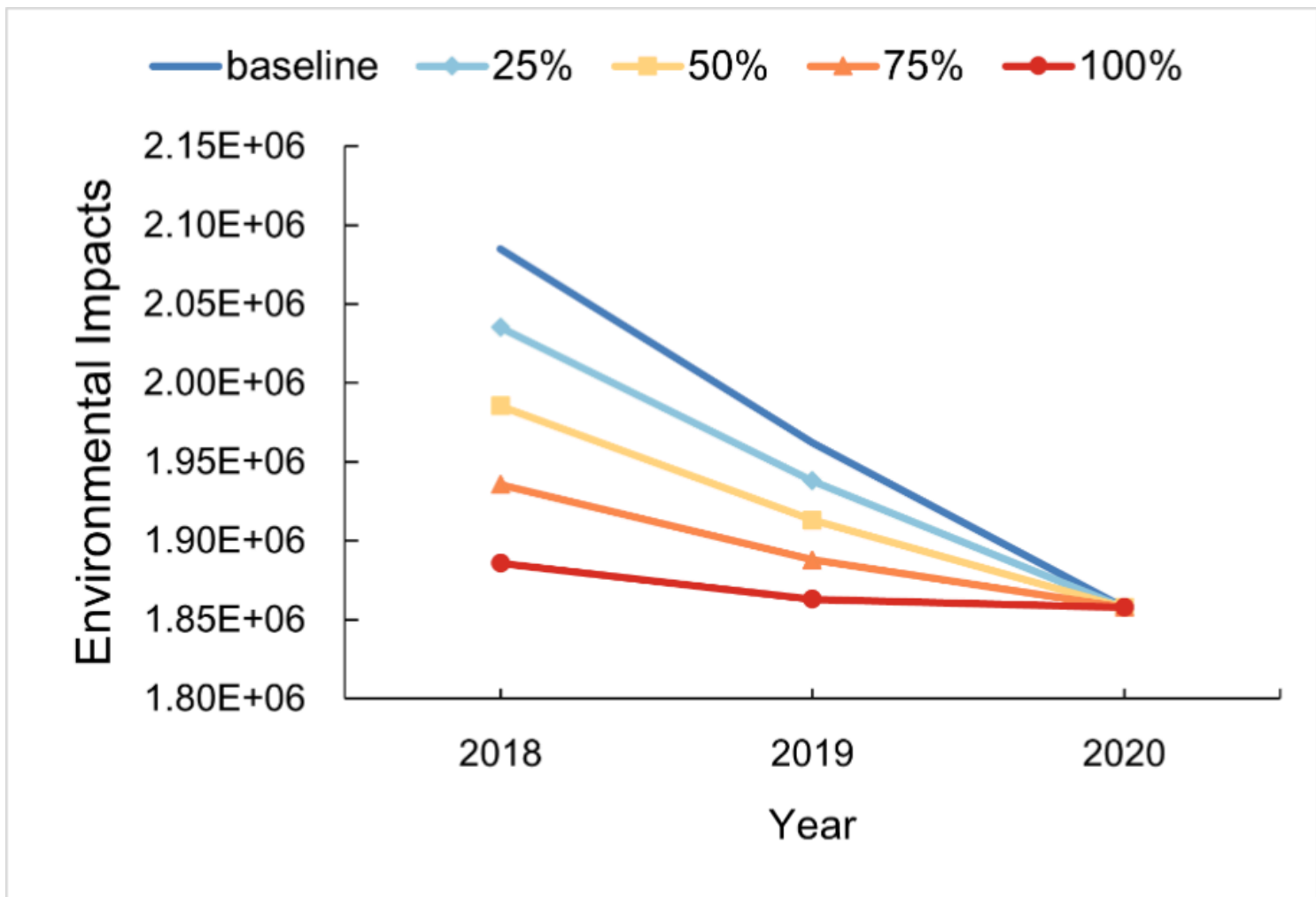


Figure 6

Environmental impacts under different initial dormitory allocation strategy optimization scenarios

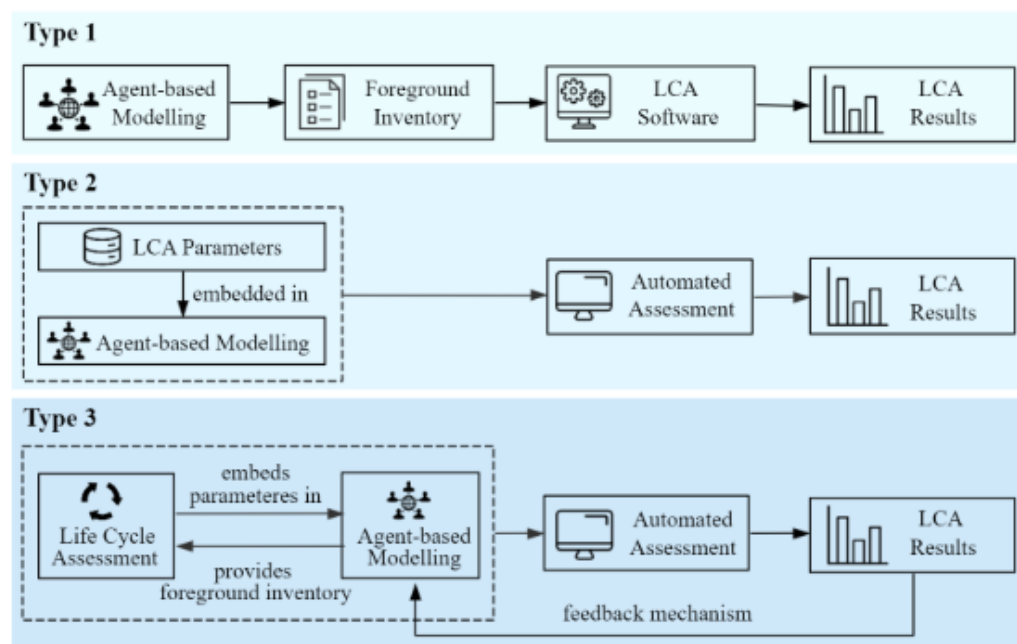


Figure 7

Three different integrations of ABM and LCA

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