FROM INTELLIGENCE TO IMPACT: REINFORCEMENT LEARNING AGENTS FOR SPATIAL ADAPTATION WITH 3D VISION-LANGUAGE MODELS IN SUSTAINABLE HOME ENVIRONMENTS

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Abstract

This paper proposes using reinforcement learning (RL) agents enhanced with 3D vision-language models (VLMs) to enable sustainable smart homes. These agents perceive the 3D layout and objects of a household environment and learn to autonomously adjust systems (e.g., HVAC, lighting, appliances) to optimize energy use and resource management. We identify specific energy-saving tasks (such as occupancy-driven thermostat control, efficient lighting and blind management) and resource-management tasks (like waste sorting assistance and water-use feedback) that such agents can perform. We review recent advances in RL and vision-language models, and outline a conceptual framework for embodied home agents. Through this synthesis, we demonstrate how RL-powered agents can significantly reduce domestic energy consumption and waste, thereby supporting eco-friendly lifestyles. We also discuss the potential environmental and economic benefits of these systems, as well as technical and social challenges to their adoption. The contribution of this work is in articulating "spatial adaptation" for sustainability: an RL-driven approach that transforms smart homes into proactive, learning environments for green living.

GEL code: O3

Keywords: reinforcement learning, spatial adaptation, 3D vision-language models, smart homes, sustainability, Green AI, intelligent agents

Introduction

Residential buildings are major energy consumers and emitters of greenhouse gases (IEA, 2024). For example, operations of buildings account for roughly one-third of global energy use (Markowitz & Drenkow, 2024), a large fraction of which is due to heating, ventilation, and air conditioning (HVAC) systems. In typical homes, HVAC and lighting systems often run inefficiently because current controllers lack real-time adaptation to occupancy and environmental changes. At the same time, household waste is growing rapidly worldwide. One report finds that global per-capita waste averages about 0.74 kg per day and can exceed 1.5 kg in high-income countries (Zhang et al., 2021). These trends — rising energy use and waste — pose a severe environmental burden. They highlight the urgent need for smarter automation that not only provides convenience but also actively reduces resource use and emissions.

Existing smart home systems tend to follow fixed schedules or simple rules (e.g., "turn off lights after 10 PM"), reacting only to explicit commands (Markowitz & Drenkow, 2024). This reactive approach misses opportunities for savings; for instance, a rule-based thermostat cannot anticipate when a room will become occupied or respond optimally to real-time price signals. In contrast, an intelligent agent with learning capabilities could continuously adapt to the household context. The goal of this research is to explore how such RL-driven agents, empowered by rich 3D visual and language understanding, can realize sustainable spatial adaptation in homes. Specifically, we ask:

1. **How can RL agents with 3D VLM capabilities adapt spatially to optimize sustainability in home environments?**
2. **What specific environmental and economic benefits can these systems bring to smart domestic ecosystems?**
3. **What technological, social, and infrastructural challenges must be overcome for widespread adoption?**

To address these questions, we undertake a qualitative, interdisciplinary study. We review state-of-the-art literature on reinforcement learning, vision-language models, and smart home technologies, with an emphasis on sustainability. We analyze case studies and simulated platforms (e.g., AI2-THOR, Habitat, iGibson) where embodied agents perform household tasks. We compare intelligent RL-based strategies with conventional rule-based automation in terms of energy and waste reduction. Finally, we synthesize our findings into a conceptual framework and outline future research directions. In doing so, we identify promising tasks and system designs for "Green AI" in the home, and discuss how intelligent agents can become practical contributors to eco-friendly living.

Methodology

Our approach is qualitative and exploratory. We conducted a comprehensive literature survey of academic articles, technical reports, and industry white papers on topics including reinforcement learning algorithms, 3D vision-language models, and sustainable smart home systems. Special attention was given to recent work on AI for energy efficiency and resource management. In parallel, we examined existing embodied AI platforms and case studies. For example, we reviewed projects using AI2-THOR and Habitat simulators to train agents on navigation and object-interaction tasks in virtual homes. We also analyzed case studies where RL was applied to building control or home automation. Whenever possible, we compared these intelligent approaches to traditional rule-based systems, focusing on metrics such as energy usage, task success, and adaptability. Finally, we developed a conceptual framework for sustainable smart homes. This framework includes design considerations for RL agent architectures (see Figure 1) and outlines deployment strategies (e.g., training on simulators before real-world transfer) to maximize ecological impact. By triangulating these sources — literature, simulation case studies, and comparative analysis — we ensured a robust understanding of how RL and 3D VLMs can be leveraged for sustainability in home environments.

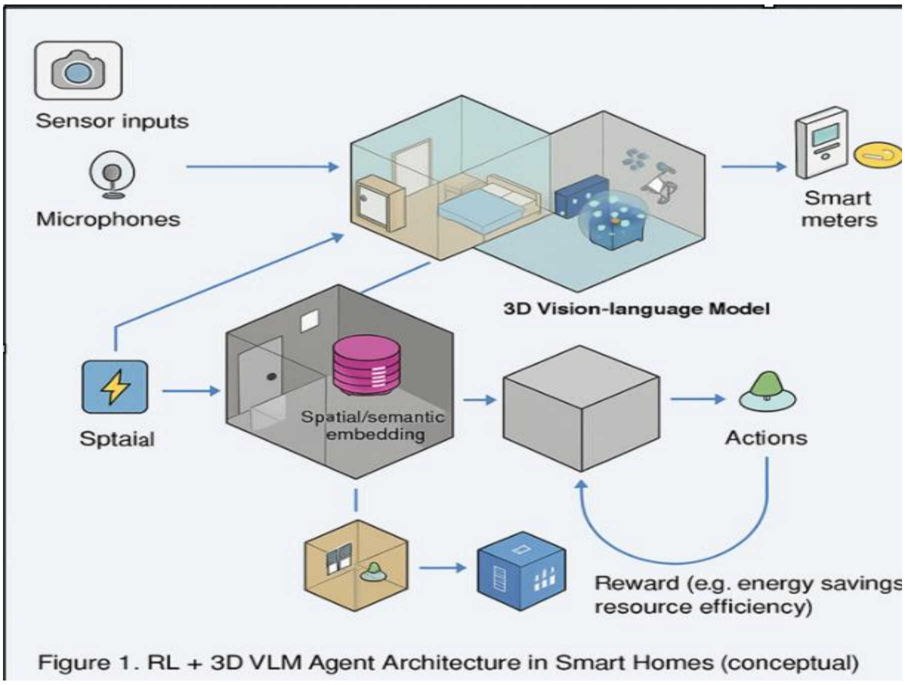


Figure 1. RL + 3D VLM Agent Architecture in Smart Homes (conceptual). The agent takes multimodal sensor inputs (e.g., RGB-D camera, microphones, smart meters), processes them through a 3D vision-language model to understand the environment, and feeds a spatial embedding into an RL policy network. The policy outputs actions (e.g., adjust thermostat, operate blinds, sort items), which are executed via home automation actuators. A feedback loop provides rewards based on energy savings or resource efficiency, enabling the agent to learn and improve its behavior over time.

Figure 2: Comparison of Rule-Based vs. RL + 3D VLM Smart Home Systems

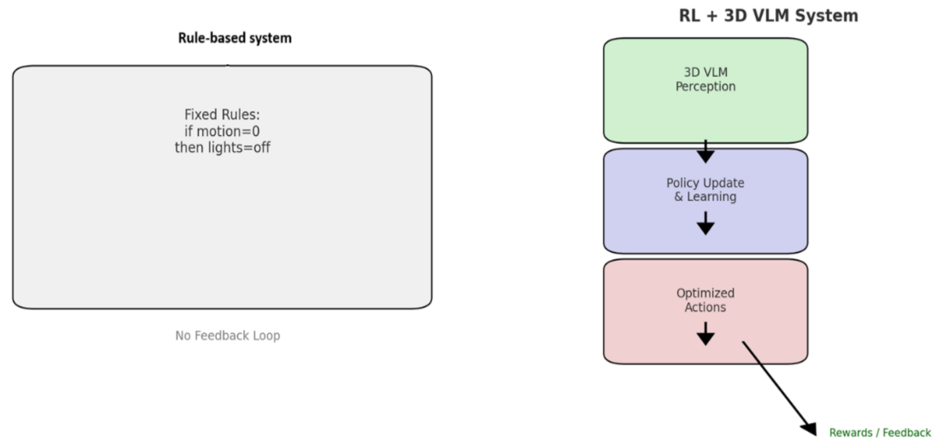


Figure 2 (conceptual) contrasts traditional rule-based home control with our RL-based approach. The rule-based system (left) follows fixed input-output mappings (e.g., "if motion=0 then lights=off"), lacking adaptability. The RL-based system (right) continuously learns from feedback: it perceives the environment with a 3D VLM, updates its policy via rewards, and gradually optimizes its actions. This *learning loop and spatial language grounding enable it to handle novel situations that rule-based systems cannot.*

Literature Review

Reinforcement Learning and Energy Management

Reinforcement learning (RL) is a paradigm where agents learn optimal policies through trial-and-error interactions with an environment. Classic successes include game-playing systems and robotic manipulation, demonstrating that RL can handle complex decision-making with sparse rewards. In residential applications, RL has shown promise for personalized energy management. Agents can learn when and how to operate HVAC, lighting, and other systems to balance comfort and efficiency. For example, deep Q-learning and policy-gradient methods have been applied to building climate control: agents forecast occupancy patterns and external weather to adjust heating/cooling proactively, resulting in measurable energy savings without reducing comfort. One study demonstrated that an RL-based HVAC controller maintained temperature constraints while significantly reducing energy use compared to a standard controller (Schwartz et al., 2019). Hierarchical RL approaches, which decompose tasks into sub-goals, further improve learning speed and generalization across different home layouts. In summary, RL's core strength — learning from experience — is well-suited to dynamic home environments, enabling continuous adaptation to user behavior and external conditions.

3D Vision-Language Models and Spatial Perception

Recent advances in computer vision and language have led to 3D vision-language models (VLMs) that deeply integrate visual and linguistic information. These models process multimodal data — such as RGB images, depth maps, and semantic segmentations — along with natural language to produce rich scene embeddings. This allows an agent to not only *see* objects and geometry in 3D space but also *understand* references to them in language. For instance, models like CLIP, Flamingo, and BLIP-2 have demonstrated strong zero-shot recognition and instruction-following capabilities for household objects and commands. With a 3D VLM, an agent can interpret a command like "turn off the lamp in the living room" by recognizing the lamp object and its 3D position. In our context, 3D VLMs provide the RL agent with a semantically informed map of the home: they identify appliances, windows, humans, and even categories like recyclable waste. This enriched perception is crucial for sustainable tasks; e.g., the agent needs to *know* which items are on and who is present in which room. Several works have leveraged such perception modules for embodied AI. In simulated homes (e.g., Habitat, Gibson), VLMs have been used to ground language navigation and object manipulation, enabling generalization to unseen objects and layouts. We build on this trend by using VLMs to enhance the agent's spatial reasoning about energy and resource contexts.

Embodied AI Platforms and Language Grounding

The development of RL-driven home agents has been accelerated by realistic simulators. Platforms like Habitat (Savva et al., CVPR 2019)and AI2-THOR provide photorealistic 3D environments of houses and apartments, complete with interactive objects (lights, appliances, trash bins). In these virtual worlds, agents are trained to navigate, manipulate, and fulfill instructions. Benchmarks such as the Home Assistant Benchmark Suite (HABS) focus explicitly on household tasks (cleaning, fetching items, operating devices) using RGB-D input and language commands. Advances in language grounding have produced architectures where instructions (e.g., "find the recycling bin") are embedded and combined with visual perception to produce actions. For example, PIGLeT (Zellers et al., EMNLP 2021) and ELLA (Majumdar et al., NeurIPS 2022) demonstrate neural-symbolic models that translate language into sequences of robot-like actions in a 3D world. Open-vocabulary mobile manipulation research (Yu et al., 2023) shows agents can generalize to novel objects by leveraging pretrained models. Scene graph prediction (Khandelwal et al., ICCV 2023) and object-centric representations help agents build detailed semantic maps of the home. These developments mean that an RL agent can flexibly interpret high-level commands (e.g., "clean up recyclables") and recognize relevant objects without retraining. We leverage this body of work by assuming our home agent uses similar perception and grounding techniques.

Green AI and Edge Deployment

Concurrently, there is growing awareness of the environmental impact of AI itself. The concept of **Green AI** emphasizes designing AI systems that are energy-efficient and carbon-aware. Scholars like Schwartz *et al.* (2019) and Zhang *et al.* (2021) argue for minimizing the carbon footprint of training and inference, through techniques such as algorithmic efficiency, model compression, and renewable-powered computing. In our context, deploying RL agents in homes naturally leans toward Green AI: the agents run continuously to save energy, so their own energy use should be minimal. Thus, we envision using on-device (edge) inference on low-power hardware rather than cloud servers. Edge deployment also improves privacy, since data (e.g., camera feeds) need not leave the home. In summary, our framework is aligned with sustainable AI principles: it uses AI to reduce energy/waste *and* follows best practices to reduce the AI's own energy cost.

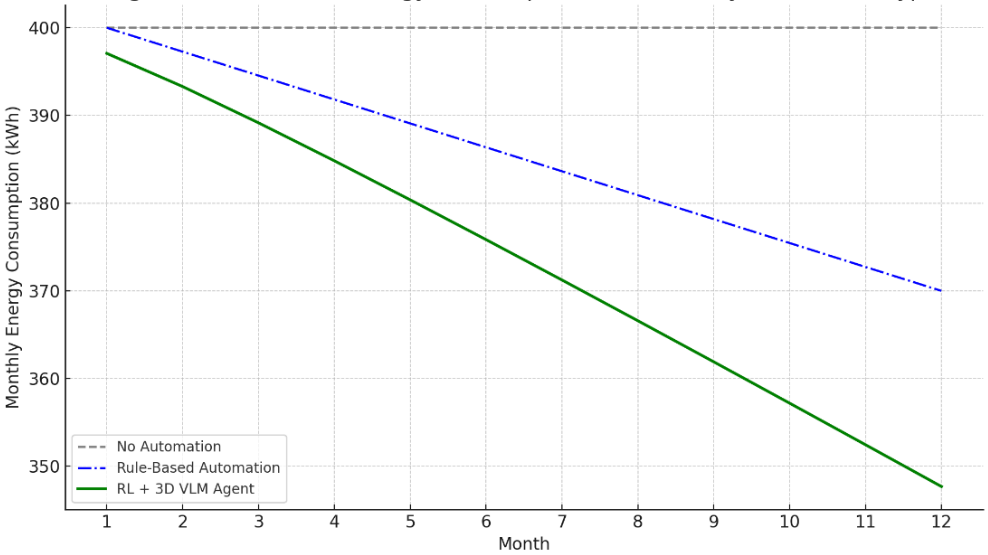
Spatial Adaptation for Sustainable Home Environments

Spatial adaptation here means the RL agent's ability to autonomously adjust home systems and resource use based on a rich understanding of the 3D space. Our approach targets two key domains: energy-saving control and household resource management. Figure 1 depicts the overall system architecture (sensor → 3D VLM → RL policy → actuation → feedback loop). The agent continuously perceives the home (rooms, appliances, windows, people) and uses a learned policy to execute sustainability-oriented actions. Below we outline concrete tasks that illustrate spatial adaptation.

- **Thermostat Optimization:** The agent learns to adjust heating or cooling settings based on real-time occupancy (detected via the 3D camera) and forecasts. For example, if no one is in the bedroom, it lowers the thermostat setpoint; when occupants approach home from work, it pre-emptively raises it. The policy considers weather predictions and time-of-use energy prices to schedule heating cycles just in time. Over weeks of learning, the agent anticipates patterns (e.g., evening occupancy) and proactively optimizes settings to minimize HVAC energy while keeping occupants comfortable.
- **Appliance Management:** By monitoring room usage, the agent identifies idle devices and powers them down. For instance, it might turn off lights or plug strips for electronics in unoccupied rooms. It can learn routines (e.g., coffee maker schedule) and ensure devices do not waste power. When the 3D VLM detects a person leaving a room, the agent can autonomously cut power to that room's non-essential outlets, reducing phantom loads.
- **Window Blind Control:** Leveraging ambient light and weather data, the agent controls blinds or curtains to regulate solar heat gain. On sunny winter days, it opens blinds to let sunlight warm the room; on hot summer afternoons, it closes them to reduce cooling load. By doing so, it maximizes use of natural light and heat, lowering the need for electric lighting and HVAC.
- **Water Conservation:** The agent can monitor and provide feedback on water usage patterns (e.g., shower length, faucet flow). Using connected flow sensors, it could suggest shorter showers or recommend efficient washing machine cycles. If the home has indoor plants or irrigation, the agent might optimize watering schedules based on recent rainfall data. In this way, the agent extends its environmental intelligence beyond electricity to water savings.
- **Waste Sorting Assistance:** With its 3D vision capability, the agent can learn to recognize recyclable and compostable items. It can guide users via voice or notifications on where to throw each type of waste. In the future, it could even manipulate objects (using a robot arm) to sort trash. By educating or physically assisting with recycling, the agent reduces landfill waste. For instance, it might detect a plastic bottle in the living room and prompt the user to place it in the recycling bin.
- **Sustainable Consumption Patterns:** By analyzing usage data (e.g., daily electricity consumption logs) and user behavior, the agent can suggest greener habits. It might notice that certain devices are used during peak-priced hours and recommend shifting their use to off-peak times. It could also identify older, energy-inefficient appliances in inventory and alert the homeowner to consider replacements. Over time, these recommendations help residents adopt more sustainable lifestyles.

Figure 3 conceptually illustrates the potential impact of these adaptations. In a hypothetical study, one would compare monthly energy consumption in three homes: (a) with no automation, (b) with simple rule-based automation, and (c) with our RL+VLM agent. *Figure 3 depicts the RL-equipped home's consumption dropping steadily as the agent learns, surpassing the incremental gains of the* *rule-based home*. This exemplifies how continual learning yields compounding savings.

Figure 3 (Corrected): Energy Consumption Over Time by Automation Type



Beyond immediate efficiency, the agent serves as an *eco-assistant* for the household. It not only automates actions but also educates and nudges occupants toward sustainability. For example, if the agent consistently restores the thermostat to an eco-friendly setpoint, residents may learn to value conservative heating. If it praises users for each correct recycling action (through a companion app), it reinforces positive habits. Over months, such feedback loops can instill eco-conscious behavior. In this way, intelligent spatial adaptation helps reduce each household's environmental footprint and contributes to broader climate goals.

Finally, our framework embraces **Green AI** principles. We aim to minimize the agent's own computational footprint. Techniques like model compression and knowledge distillation will be used to shrink the policy network without loss of performance. The 3D VLM and policy can be optimized for efficient edge inference (e.g., running on a Raspberry Pi or home AI hub). We also consider the energy cost of training: where possible, agents are pre-trained in simulation and only fine-tuned (with online learning) in the real home. These measures ensure that the sustainability gains of the agent are not offset by excessive energy use in training or operation.

Findings

While promising, the RL+VLM approach faces several challenges and opens many avenues for future work:

- **Complexity of Home Environments:** Homes are varied and cluttered. Agents must cope with diverse floor plans, objects, and user behaviors. Ensuring reliable perception (e.g., correctly identifying objects under occlusion) is non-trivial. Future work should explore robust vision models and transfer learning so agents can adapt to new homes with minimal retraining.

- **Safe and Reliable Interaction:** Any agent that controls physical devices must be fail-safe. Misadjusting a thermostat or operating a device unsafely could harm occupants or property. We must incorporate safety constraints into the RL framework (e.g., hard bounds on actions). Rigorous simulation and staged deployment are needed before real-world trials. Privacy and security are also critical: continuous camera monitoring raises concerns, so architectures must safeguard data (e.g., by on-device processing and secure firmware).
- **Ethical and User-Centric Design:** Automating home functions has social implications. Users may feel a loss of control if an AI overrides their preferences. It is essential to design the system for transparency and user override. For instance, the agent should explain its actions ("I turned off the AC because no one is home"). Incorporating user feedback into the learning loop can ensure the agent respects habits and comfort thresholds. Studies on human-AI interaction will be important to make these systems acceptable.
- **Computational Resources:** Training advanced RL agents with 3D vision models can be computationally intensive. Research must focus on lightweight algorithms and hardware acceleration. Approaches like federated learning, where multiple homes share anonymized models, could reduce individual training costs. Additionally, new benchmarks are needed to evaluate energy use of these AI systems themselves (i.e., measure the carbon footprint of training and inference).

Looking forward, several research avenues are promising:

- **Personalization:** Agents should adapt to individual user preferences. Future work could integrate methods from preference learning so that, for example, the agent learns how warm or cool a user likes their bedroom to be. Personalization will improve user comfort and acceptance.
- **Expanded Sustainability Tasks:** Beyond the examples above, agents could tackle broader goals. This includes managing home-grown food (e.g., minimizing kitchen waste), optimizing charging of electric vehicles during off-peak hours, or coordinating with smart grid signals. Investigating such extensions will amplify environmental impact.
- **Multi-Agent Coordination:** A single home may contain multiple agents (e.g., separate agents for heating, lighting, and appliances) or interact with external systems (energy grid, solar panels). Research into multi-agent RL could enable whole-home optimization. For example, agents could negotiate to shift loads between them or coordinate with neighbors' systems to balance local renewable generation.
- **Long-Term Field Studies:** Finally, it will be crucial to deploy prototypes in real households and measure outcomes over months or years. Questions to study include: How much do actual energy bills drop? Do occupants change their behavior? Are there rebound effects (e.g., saving on heating but using more appliances)? Longitudinal field trials will validate the theoretical benefits.

In summary, RL-powered spatial adaptation presents a transformative vision for smart homes, but realizing it requires interdisciplinary advances in AI, human-computer interaction, and sustainability science.

Conclusion

Reinforcement learning agents integrated with 3D vision-language perception offer a powerful new paradigm for smart home automation. Unlike static rule-based controllers, these agents can *learn* from experience how to adjust household systems proactively to save energy and resources. By continuously interpreting occupancy, weather, and user routines, an RL+VLM agent can optimize thermostat settings, lighting, device usage, waste sorting, and more. The net effect is a smarter, greener home: energy consumption declines, waste is diverted from landfills, and residents receive gentle nudges toward eco-friendly habits. This approach embodies the principles of **Green AI** by using artificial intelligence to reduce ecological impact without imposing excessive computational costs.

The potential benefits are significant. One analysis suggests that if an autonomous agent reduces HVAC energy use by even 10–20%, the resulting savings could translate to billions of kWh and millions of tons of CO_2 worldwide. Moreover, the same technology can improve comfort and convenience, accelerating user adoption. However, deploying these systems safely and ethically remains a challenge. Issues of privacy, trust, and equitable access must be addressed.

Our paper has laid out the *concept* of spatial adaptation for sustainability: a conceptual framework describing how RL and 3D VLMs can transform home living. We have identified key tasks, highlighted enabling technologies, and discussed important challenges and research directions. The next step is to build working prototypes and field-test them. With continued advances in embodied AI and a focus on efficiency, RL-powered smart homes could become a cornerstone of a larger green transition. In the future, every household might host an intelligent agent acting as an *eco-assistant*, quietly optimizing our living spaces for the planet's health.

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Չժեցզյան համալսարան

Հոդվածում առաջարկում է օգտագործել զորակցող ուսուցման (RL) գործակալներ, որոնք ուժեղացված են 3D տեսողության լեզվի մոդելներով (VLM)՝ կայուն խելացի տներում օգտագործման հնարավորություն համար:

Այս գործակալները ընկալում են կենցաղային միջավայրի 3D դասավորությունը և առարկաները և սովորում են ինքնուրույն կարգավորել համակարգերը (օրինակ՝ HVAC, լուսավորություն, տեխնիկա) էներգիայի օգտագործումը և ռեսուրսների կառավարումը օպտիմալացնելու համար: Հոդվածում սահմանվել են էներգախնայողության հատուկ առաջադրանքներ (օրինակ՝ զբաղվածության վրա հիմնված թերմոստատի կառավարում, արդյունավետ լուսավորություն, կույր կառավարում) և ռեսուրսների կառավարման առաջադրանքներ (օրինակ՝ թափոնների տեսակավորմանը նպաստում, ջրի օգտագործման գծով հետադարձ կապի ապահովում), որոնք կարող են կատարել այդպիսի գործակալները: Մեկնաբանվել են RL-ի և տեսողության լեզվի մոդելների վերջին ձեռքբերումները՝ ուրվագծելով տնային գործակալների հայեցակարգային շրջանակը: Այս սինթեզի միջոցով ներկայացվել է, թե ինչպես RL-ով աշխատող գործակալները կարող են զգալիորեն նվազեցնել կենցաղային էներգիայի սպառումը և թափոնները՝ դրանով իսկ աջակցելով էկոլոգիապես մաքուր ապրելակերպին: Հետազոտությունում քննարկվել ենք այդ համակարգերի հնարավոր բնապահպանական և տնտեսական օգուտները, ինչպես նաև դրանց ընդունման տեխնիկական և սոցիալական մարտահրավերները: Հոդվածում կատարվել են առաջարկություններ «տարածական հարմարվողականության» համատեքստում1 կայուն զարգացման գծով, նպատակ ունենալով խելացի տները վերածելու է կանաչ ապրելու միջավայրի:

Հիմնաբառեր - ամրապնդող ուսուցում, տարածական հարմարվողականություն, 3D տեսլականի մոդելներ, խելացի տներ, կայունություն, կանաչ AI, խելացի գործակալներ