Sustainable Machine Intelligence Journal

Journal Homepage: sciencesforce.com/smij

Sustain. Mach. Intell. J. Vol. 8 (2024) 1–13

Paper Type: Review Article

Responsible Artificial Intelligence for Climate Action: A Theoretical Framework for Sustainable Development

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Received: 15 Feb 2024 **Revised:** 29 Apr 2024 **Accepted:** 24 May 2024 **Published:** 03 Jun 2024

Abstract

Climate change poses an urgent and significant challenge, with far-reaching impacts already affecting our planet, and projections indicating worsening conditions in the future. The concept of sustainable development aims to meet present needs while safeguarding the ability of future generations to meet their own requirements. However, climate change's effects on sustainable development are of paramount concern, as they amplify issues like poverty, food insecurity, and environmental degradation, affecting economic growth, social progress, and environmental protection. Taking immediate action to mitigate climate change and implement sustainable practices is crucial to ensuring a habitable planet for future generations. In this context, Responsible Artificial Intelligence (RAI) emerges as a promising direction, striving for ethical and responsible technology use in diverse sustainable development tasks. RAI proves to be a robust candidate for empowering climate change mitigation and adaptation efforts. This study introduces a theoretical RAI framework designed to support climate action by responsibly enabling more accurate predictions and analysis of climate data, enhancing energy efficiency, and reducing greenhouse gas emissions. The framework emphasizes the need for interdisciplinary collaboration among policymakers, scientists, and technicians to develop RAI solutions that advance sustainable development and alleviate the adverse impacts of climate change. Unlike previous works, this research presents a novel perspective on the principles of RAI that explicitly consider climate-related aspects. By laying the foundations of AI research to bolster our fight against climate change, this article establishes essential pillars that encourage further advancements in this critical endeavor.

Keywords: Climate Change; Artificial Intelligence; Sustainable Development; Machine Learning.

1 | Introduction

Global Vision 2030 presents the international sustainable development strategy (SDS) for comprehensive development in different sectors of the country, aiming to revive the role of countries in regional and global leadership. This strategic vision was established based on a tactical planning method under cooperation between local and global development associates, civilization representatives, and governments, which established inclusive objectives for all axes of human life [1]. For preserving the rights of the next generations in the good life, the SDS emphasizes three key axes namely the economic, social, and environmental. When it comes to the environmental axis, Climate change obviously turned out to be the severest factual threat confronting our planet nowadays. Floods, droughts, storms, ice quakes, and fires have come to be more

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https://doi.org/10.61356/SMIJ.2024.88101

common and stronger [2]. Accordingly, universal ecosystems are witnessing substantial changes in the natural resources that human beings depend on [3]. In 2018, the intergovernmental report on climate change expected that humanity will encounter disastrous consequences except if the emissions of global greenhouse gas (GHG) are eradicated in the next thirty years. However, the rate of emissions increases one year after another. Also, the Intergovernmental Panel on Climate Change has reported that postponing addressing this threat is no longer possible.

Tackling the challenges of climate change includes two directions namely mitigation (which means decreasing the emissions) and adaptation (getting ready for unescapable effects). Each of them is a multidimensional solution. Mitigating the emissions of GHG necessitates modifications and updates of the transportation system, power systems, industry, urban system, and agriculture and farming. In another way, adaptation necessitates preparation for elasticity and catastrophe management, based on a deep interpretation of climate and relevant extraordinary actions. This multi-facet nature of both directions could be perceived as a prominent research gap as there are numerous ways to investigate in this regard [4].

Recently, Artificial intelligence (AI) that is demonstrating great technological achievements in a broad range of applications. In spite of the recent advances in the applications of DL to solve societal issues and global good problems, there is a critical need for intensive exertion to recognize the best way to effectuate AI might be applied for achieving climate-friendly sustainable development [5]. In 2015, the United Nations General Assembly (UNGA) defined seventeen sustainable development goals (SDGs) to join in the three axes of SDS. SDGs are globally decided priorities for socially valuable action and hence establish a satisfactorily experimental and practically uncontended benchmark to gauge the optimistic influence of AI in supporting supports the SDGs, which is named AI×SDGs. By reviewing the academic and non-academic databases, we found that the literature contains 263 research projects investigating the SDGs acrossdifferent countries. Among them, our recent survey study identified 183 AI×SDG projects as reported in publicly available databases of the Oxford Research Initiative on SDG and AI [2-6].

Figure 1. Statistics distribution of AI×SDGs projects across different SDGs.

Figure 1 analytically illustrates the number of AI projects devoted to addressing every SDG, and it is noticed that the adoption of AI×SDG projects witness an international interest from different countries in five continents how this interest may not be similarly circulated across the SDGs (SDG-1= No poverty, SDG-2=Zero hunger, SDG-3=Good health and well-being, SDG-4= Quality education, SDG-5=Gender equality, SDG-6= Clean water and sanitation, SDG-7= Affordable and clean energy, SDG-8=Decent work, and economic growth, SDG-9= Industry innovation, and infrastructure, SDG-10=Reduced inequalities, SDG-11= Sustainable cities and communities, SDG-12=Responsible consumption and production, SDG-13=Climate action, SDG-14= Life below water, SDG-15= Life on land, SDG-16= Peace. Justice and strong institutions, SDG-17= Partnerships for the goals). Among the abovementioned goals, it is notable that climate action gains considerable focus with a total of 19 AI×SDG projects. Other SDGs that relate to climate change (i.e., clean water and sanitation, Affordable and clean energy) are considered by some AI×SDG projects. It is worth mentioning that the above statistics demonstrate the adoption of AI to address any of the SDGs without essentially leading to success.The study [2] overviewed the applications of AI in different applications that directly or indirectly help combat climate change through either innovative research or active engineering. The tabulated findings are based on reviewed literature studies including those reported by [3]. As noted, the table focuses only on the areas in which the ML is applicable and ignores other areas. Despite the promise of DL in solving many environmental challenges, there is no available solution to address climate change. Surprisingly, climate change might be worsened when AI is applied in a non-climate-friendly manner.

Climate change poses significant challenges to SDG, which aims to meet the needs of the present without compromising the ability of future generations to meet their own needs. However, climate change threatens this goal by exacerbating issues such as poverty, food insecurity, and environmental degradation. Climate change impacts all aspects of SDG, including economic growth, social progress, and environmental protection [7]. Rising temperatures and extreme weather events such as floods, droughts, and storms can lead to crop failure, loss of livelihoods, and displacement of people. This, in turn, can lead to food insecurity, poverty, and social unrest. Climate change also puts pressure on natural resources such as water and biodiversity, leading to environmental degradation and loss of ecosystem services. This can impact economic activities such as agriculture, forestry, and fisheries, and further exacerbate poverty and social inequality [1-3]. To address the challenge posed by climate change to sustainable development, it is essential to take immediate action to mitigate greenhouse gas emissions, enhance climate resilience, and promote sustainable development practices [4].

In response to the above challenges, this study seeks to contribute to the body of knowledge as follows:

- First, this work presents a new theoretical framework for responsible AI for combating climate change should include several key ethical principles such as transparency, accountability, fairness, and privacy, which ensure that AI is used responsibly, and its benefits are distributed equitably.
- Our framework should align with the sustainable development goals, particularly goal 13 (climate action), to ensure that AI solutions support efforts to mitigate the impacts of climate change.
- Our framework suggests that interdisciplinary collaboration among policymakers, scientists, and technologists is crucial in creating responsible AI solutions that promote sustainable development and reduce the negative impacts of climate change.
- Our framework should prioritize the development of AI solutions that enable accurate climate modeling and forecasting, enhance the energy efficiency, reduce greenhouse gas emissions, and support the transition to renewable energy sources, and it should also consider the potential social and environmental impacts of AI and ensure that these technologies are deployed in a manner that is socially just and environmentally sustainable.
- Driven by the above, we introduce a road map to promote the research community to develop intelligent and responsible AI solutions to defend against climate change. The proposed road map provides the AI community with opportunities for integrating the RAI with other technologies to further empower the lines of defense against climate change either through mitigation or adaptation.

The remainder of this paper is organized as follows. Section 2 introduces the principles of responsibility in the RAI framework. Section 3 projects the roadmap for the responsible development and deployment of AI solutions for combating climate change. Section 4 concludes our research.

2 | Background and Literature

The responsible AI principles refer to the practical framework established based on the agreement of domain experts to deliver guidance for technologists to develop AI systems dependably [5]. In this section, we define a new responsible AI framework according to environmental perspectives aiming to empower scholars and practitioners to develop responsible and climate-friendly AI solutions. In the following, we figure out the main pillars of the proposed responsible AI framework (see Figure 2).

Figure 2. Systematic diagram of framework of responsible artificial intelligence.

2.1 | Explainability

In this pillar, the practitioners are committed to developing tools and methods to continually increase the transparency and explainability of machine learning models. The excitement around deep learning has led many engineers to put massive amounts of data into sophisticated ML pipelines, expecting that something will work, without knowing how the pipelines function within. As a result, it is imperative that technologists put in the time and effort necessary to continually enhance the tools and processes they use in an effort to better explain their findings. ML systems can be made more understandable by using different tools and methodologies, for as by adding domain knowledge to features rather than relying on deep/complex models to infer them. Accuracy may be reduced in certain cases yet transparency and explainability may be substantial advantages [6].

2.2 | Sustainability

It's time to go further than AI4Good and address the sustainability of designing and using AI systems in and of themselves, even while there is a rising push to drive AI usage towards "positive" ends (i.e. sustainable development goals). Studies by Strubell et al. have shown that training a particular AI model (GPU) can result in approximately 600,000 lb of carbon dioxide emissions. They are well recognized. A five-car fleet produces nearly the same amount of carbon dioxide emissions in its lifespan as a typical household does. The emissions from AI systems that could play games (or perform other menial duties) are not worth the cost, especially at a time when the globe is committed to lowering carbon emissions [7-8].

Aside from manufacturing and healthcare, AI is a technology that may be used in other industries as well. It has the potential to be just as ubiquitous as the internet and mobile phones. We can't afford to disregard the environmental repercussions of this technology. For these reasons, I believe we should focus on sustainable artificial intelligence. The RAI should establish and promote a shift toward sustainable AI as a means of connecting the dots between the creation and use of artificial intelligence and its environmental impact.

2.3 |Greenness

The pillar of the greenness of AI refers to the practice of developing AI solutions that take into consideration resource consumption. The traditional AI system has led to quickly intensifying computing (and hence carbon) costs [7]. Hence, the greenness of AI systems enables methods that exhibit promising trade-offs between performance and efficiency. As the metrics of efficiency are extensively adopted for evaluating the performance of AI solutions, the practice of AI development becomes in great need to consider the performance of models according to comprehensiveness and the environment. At this point, a variety of efficiency metrics can be stated, augmented, and support one specific metric— floating-point operations (FPO)- that must be conveyed in the practice of evaluating AI performance. It is suggested that the quantity of work necessary to produce a result be reported to gauge efficiency [7]. The community recommendation is to report the number of operations needed to reach the result of the AI system. This number figures out how much time it takes to do something with a computer Analysis of two fundamental operations (ADDITION and MULTIPLICATION) yields the result. With the use of these two operations, the FPO cost of any machine learning abstract operation could be calculated. Although FPO has been used in the before assessing a model's energy footprint, it has not yet been commonly used in the field of artificial intelligence [8]. A wide range of positive aspects characterize FPO. Because it measures the jobs performed by the running machine when a particular instance of a model is performed, it can be linked to the quantity of energy used. This is an important consideration. For the second time, FPO is agnostic to the hardware platform on which the model is executed.

All hyperparameter optimization studies, including those that only affect a single parameter or set of parameters. An eco-friendlier AI can be created by cutting down on the amount of time and effort required to process a single example, as well as by expanding and diversifying datasets. AI practitioners are urged to employ energy-efficient hardware to save money, yet the huge rise in computing expenses in recent times is mostly due to choices made in modeling and algorithms. If you want to compare the output of different models, you'll want to choose a quantity that is comparable across all the models you're using. Preferably, this metric must remain constant regardless of the hardware, time of day, or lab in which it is run. A few pioneers in machine learning (ML) were using GPUs to train neural networks a decade ago; however, GPUs of rising capability are becoming more widely available and are now being used by ML specialists all over the world. For new models, this means training on more GPUs, with more datasets, and for longer periods of time. The rising expenses of fueling this development are a direct result of this development. Current studies evaluating the climatic implications of Ai have focused on the environmental cost of training large-scale models coupled to fossil fuel-powered grids, which was the topic of this phenomenon. To sustain this discussion and strive toward establishing the tools and methods needed to evaluate the carbon emissions emitted by AI solutions, as well as to propose ways to minimize those emissions. With the increasing danger of RAI is believed that this is an important area [7-8].

3 |Roadmap of RAI in Combating Climate Change

To address the abovementioned research gaps, this section introduces a road map for applying AI solutions to address the challenges of climate change in facing the realization of SDGs in the 2030 Agenda.

3.1 | RAI for Sustainable Low-carbon Energy

According to the UNGA's recommendations, and COP26, there is a global agreement on the need to shift towards lessening the reliance on fossil fuels. These recommendations lie in the need to develop energy systems that keep friendly with climate and healthiness [9]. Solar energy is a climate-friendly form of renewable energy source that plays a vital role in accomplishing sustainable development (see Figure 3). Despite the advantage of solar energy, it encounters many threats when it comes to the consistent and steady integration into the power grids. The chief challenge facing active market saturation of solar energy resides in its high volatility and intermittent nature. Thus, accurate predictive modeling of the availability of solar energy is extremely needed for using such climate-friendly energy.

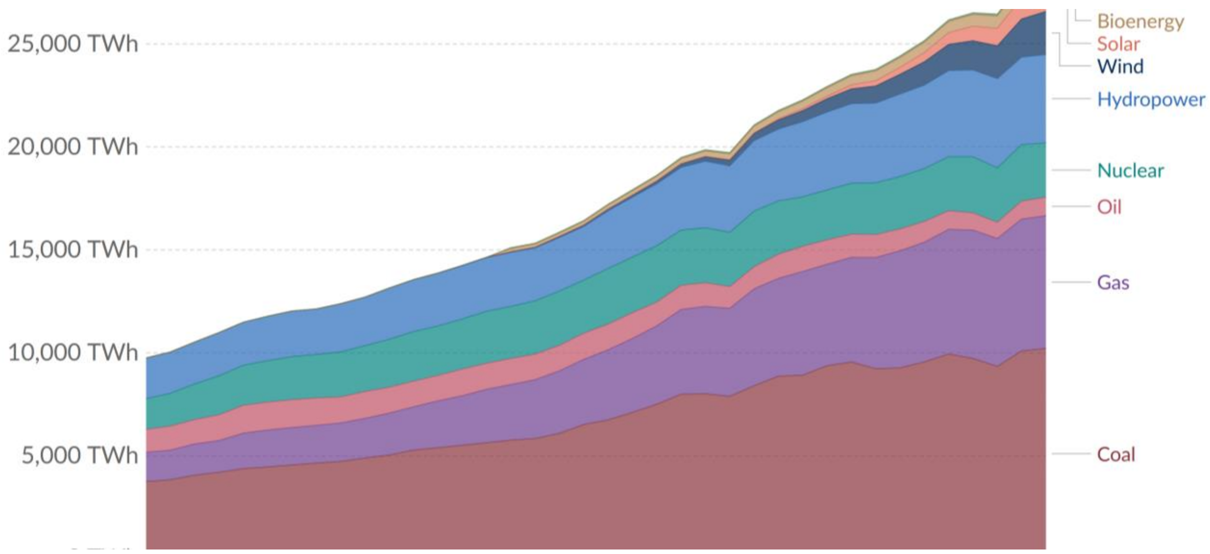

Figure 3. Statistical distributions of world's energy sources including fossil fuels and renewable energy [26].

RAI for Multi-Horizon Predictive Modeling of Solar Energy: In this step of our roadmap, we argue to present a novel responsible deep learning framework for predictive modeling of renewable solar energy from historical data in power systems. Unlike the existing studies, the RAI solution can innovatively model the future values from both photovoltaic power data as well as solar radiation data. The RAI framework can support multiple functionalities as it supports prediction at different time horizons namely ultra-short-term horizon, short-term horizon, long-term horizon, and medium-term horizon. These terms respectively support the following power grid functionalities: real-time monitoring, unit commitment, maintenance scheduling, and deployment and operations. Three design considerations are considered in this step, namely accurate predictions, resource efficiency, and interpretability of model outcomes. Accuracy is an essential metric for assessing the truth of generated predictions. Resource-efficiency of the RAI solution should help reduce the time, processing, and energy to facilitate achieving sustainability when the model is deployed in a real-world IoT system. interpretability helps the stockholders to trust and understand the generated predictions. The generated interpretations can be later exploited to improve the effectiveness of the abovementioned system functionalities [2].

RAI for multi-modal predictive modeling of solar energy

Apart from the time-series data in the previous step in our road map, the solar data is available in two formats namely spatial data and sky images (see. Figure 4). This step follows and extends the previous step by introducing a novel transformer network to conduct predictive modeling of solar irradiance from video sequences of sky images in addition to auxiliary spatial data. The prediction performance should be evaluated at different time horizons. Unlike existing studies, this step should innovatively investigate the integration of multimodal solar data (sky images and time series) for improving the ability of the power grid in predicting the future of solar power. Sky images from different data distributions present a great challenge for achieving accurate predictions. To address these issues, a novel domain adaptation technique is introduced to empower the network to learn well from out-of-distribution data, thereby improving the overall generalization capabilities [11].

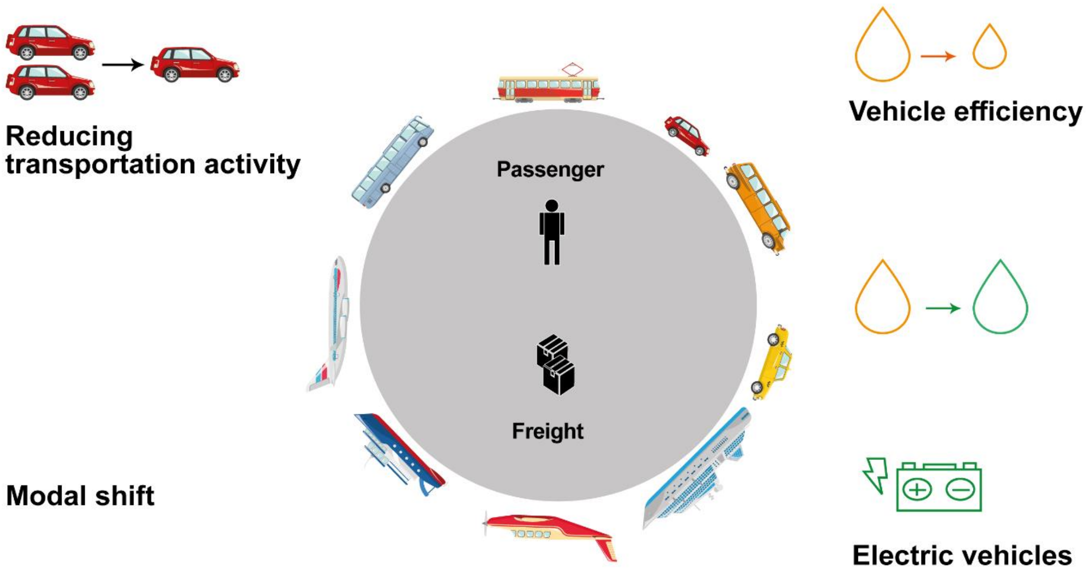

Figure 4. Systematic diagram of the opportunities of RAI in mitigating to climate change issues in transportation.

Edge-based RAI for predictive modeling in smart grids: In the previous step in our road map, it was assumed that the data is centrally located at a cloud server for training from huge data. However, the solar energy sources are distributed across the grid edge, where the solar generation, storage, and elastic loads are performed. Nevertheless, the community has many concerns regarding the security and privacy of data when the solar training data is transmitted from the edge nodes to the central server imposing many limitations on the current existing predictive modeling solutions. To address these issues, this step extends the previous step in our road map by taking the advantage of edge computing to enable distributed data owners to collaborate in training a single model without entailing any data transmission. This is simply called federated learning (FL). An innovative learning FL scheme should be investigated in this regard under both centralized FL (CFL) and distributed FL (DFL). In CFL setting should be adopted to coordinate the federated training among edge nodes. In the DFL setting, the fog or edge servers are participating and one of them to heuristically selected to coordinate the training. Unlike existing solutions, this step in our road map should scale up the predictive modeling of solar power to be accessible for remote and distant areas. Two additional design considerations are considered in this step in our road map namely privacy and scalability. Furthermore, when it comes to the integration of photovoltaic panels into distributed smart grids, two major threats are encountered namely cyber-threats (such as false data injection attacks) and losses incurred by different faults in a photovoltaic array. These challenges constitute a major barrier to the way of sustainable development of solar energy. To tackle these problems, asynchronous responsible FL is a promising direction to collaboratively train edge intelligence to detect failures and attacks in photovoltaic data/systems.

3.2 | RAI for Combating Greenhouse Gas Emissions

Resource-efficient Modeling of Geological Carbon Storage: As a way to decrease the emission rate of greenhouse gas emissions, Geologic carbon storage (GCS) has been proposed to inject huge quantities of carbon dioxide (CO_2) in deep geologic constructions to avoid incurring global climate crisis if leaked to the atmosphere. Reservoir simulation is commonly adopted in GCS reservoir supervision to forecast CO_2

saturation and subsurface pressure (See Figure 5). Nevertheless, once applied for estimating uncertainty and/or assimilating data, high-fidelity mathematical models are too costly because of the big number of needed runs. GCS solutions often encounter spatially sparse quantities from mines, resulting in extreme uncertainties in the predictive modeling of reservoir pressure. This step in our road map seeks to tackle this issue by proposing a deep learning-based pipeline to integrate surface displacement maps inferred from low-cost Interferometric Synthetic-Aperture Radar data to precisely forecast the spatial-temporal development of pressure and plumes throughout injection and periods following the injection periods of GCS operations. To promote the faithfulness of predictive modeling, different 3D deep learning models are trained for injection and post-injection periods due to the difference in the primary driving force of fluid flow and transport during these two phases. We also explore different combinations of features to predict the state variables.

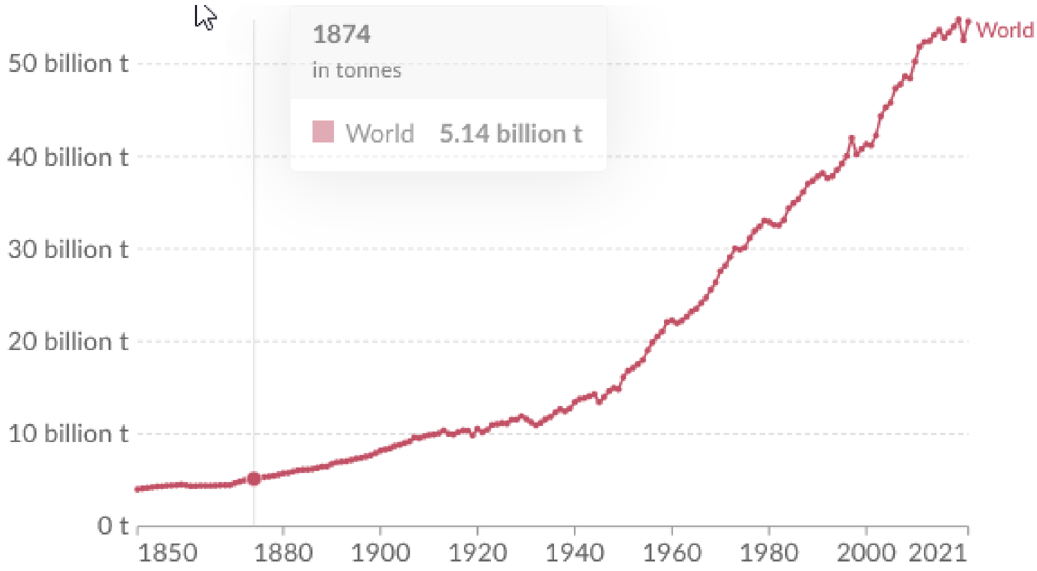

Figure 5. Statistical distributions of greenhouse gas emissions.

RAI for detecting and mitigating methane leakage using an infrared video capture: Methane is an extremely significant form of human-caused greenhouse gas impacting the climate as it is spread across all sections of the oil and gas supply chain [10]. Thus, climate change turned to show an increasing concern about the mitigation of methane leakage from the oil and gas system. To this end, the RAI is intended to present a novel responsible convolutional model for detecting methane leakage from collected infrared videos of methane leaks captured by various leaking equipment. A customized gradient activation method should be introduced to provide a visual explanation of the detection results obtained from the model.RAI for estimating methane emission source from infrared images: In the context of methane leakage, the quantification of leakage rate from experiential plumes is a serious practice to comprehend confined leakage distributions and to prioritize the extenuation exertions accordingly [11]. To achieve sustainable mitigation of methane leakage, the source of emission is required. Thus, the RAI can be designed to extend the previous model to estimate the methane's leakage sources explicitly from high-resolution infrared plume images with no dependence on metrological variables i.e., wind speeds.

Federated RAI for controlling vehicular gas emissions in sustainable smart cities: The transportation system is responsible for a large portion of emissions of greenhouse gases and thereby leading to a constant rise in global temperature. IoT is regarded as a key enabler for sustainable development in the transportation sector. In this regard, monitoring vehicular emissions is essential for regulating air pollution and controlling traffic in smart cities [12]. Nevertheless, it is challenging to forecast the temporal-spatial deviation in vehicular emission resultant from a complication of vehicular emissions as well as the temporal dependencies and spatial relations between mobile devices and roadside units (See Figure 6). Different from the existing DL methods. This step in our road map should encode the vehicular emissions according to the graph-organized traffic network. Then, a novel responsible spatial-temporal graph network is intended to model the graphical attributes characteristic (topological, spatial, temporal) from the connectivity in the traffic network and then use the learned knowledge to predict future emissions. The RAI system model considers both grounded and flying vehicles, where UAV is used here to simulate the latter category [13-16].

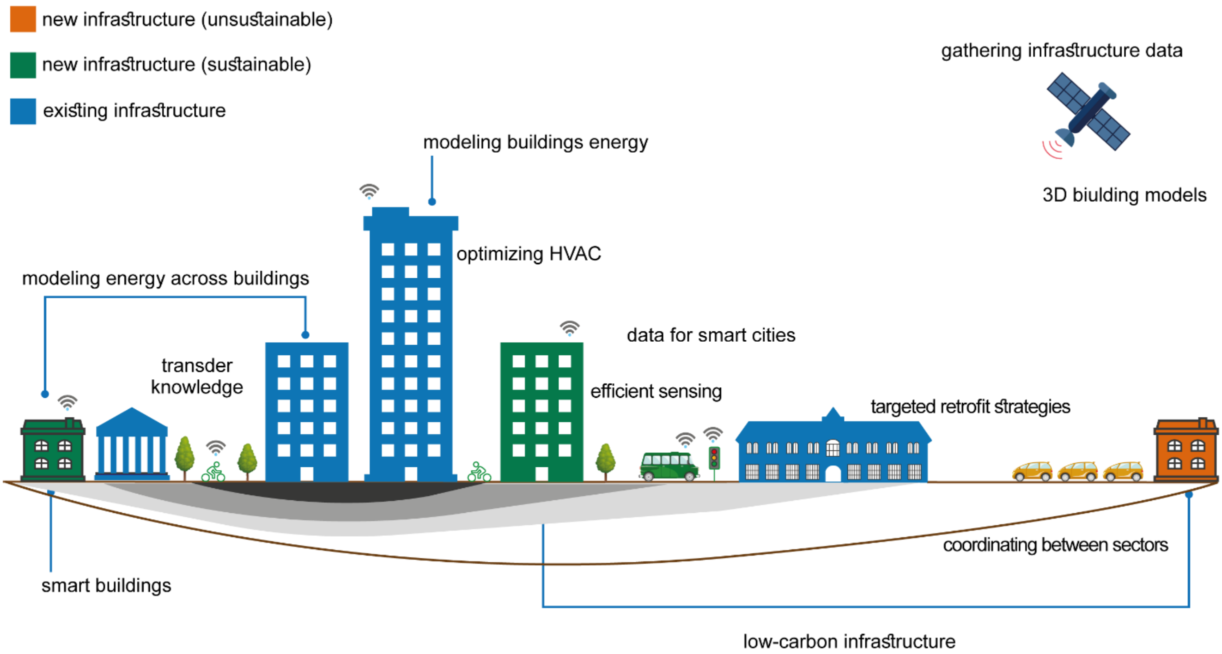

Figure 6. Systematic diagram of the opportunities of RAI in mitigating climate change issues in smart cities.

3.3 | Greening the Land

Over thousands of years, plants, bacteria, and other species have been sucking CO2 out of the atmosphere. Most of this carbon gets recycled and reprocessed in the carbon cycle, while a small amount is deposited deep in the earth. Deforestation and unproductive agriculture are major contributors to the release of trapped carbon in our existing economic system. Methane, a significantly more potent GHG than CO2, is produced by animals and rice production. About 25% of the world's GHG emissions are attributed to human activity on the soil [18]. The Arctic is melting, the peatlands are draining, and wildfires are growing more common because of climate change itself, leading to additional carbon. Because of the problem's enormous scope, a significant beneficial impact is possible. About a third of the reductions in GHG emissions might be attributed to improved land use planning and agriculture, based on a single estimation. Some of these sectors could benefit from the use of ML. To lessen deforestation, smart farming could lessen carbon emissions from the ground and boost crop yields. It is feasible to decide the quantity of carbon absorbed in certain farmland, and monitor GHG emissions from it, using satellite imagery [18-21]. ML may be used to assess the status of forests and peatlands, anticipate the fire danger, and contribute to sustainable forestry. Computer vision and machine learning (ML) technologies can have a serious influence in these sectors, but care should be provided to improve that ML tools could be used in a manner consistent with decarbonization (See Figure 7).

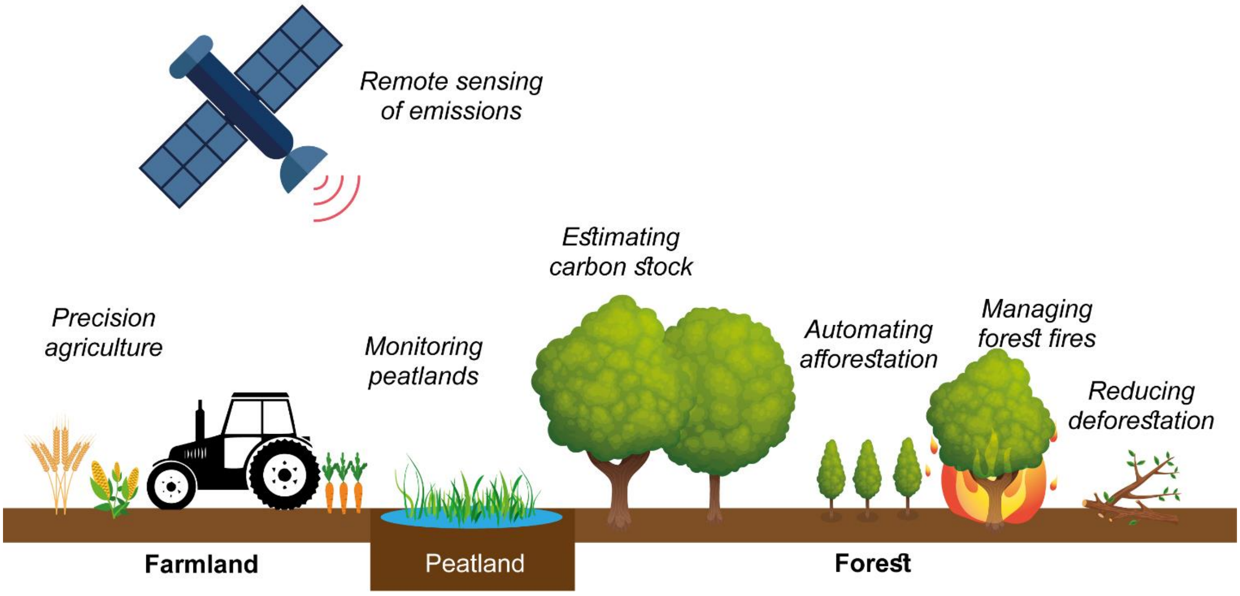

Figure 7. Systematic diagram of the opportunities of RAI in defending climate via farming and green landing.

3.4 | Social Adaption

Air pollution and climate change both affect our environment. There will be long-term ecological and socioeconomic stressors, along with brief but significant social disturbances, because of climate change. For example, crop yields could be reduced over time, leading to both a global food crisis and localized shortfalls. While this is wonderful news for society, it might be intimidating for an ML practitioner who wants to contribute to the advancement of technology. Because of this, there are some commonalities between strategies, and it is these commonalities that ML may use to help society adjust. Alarms are sounded, annotation is provided, and exchange is encouraged, all at the highest level [22-25]. To better understand how ML helps each of these climate change adaptation tactics, we'll return to these unifying themes in subsequent sections (Figure 8).

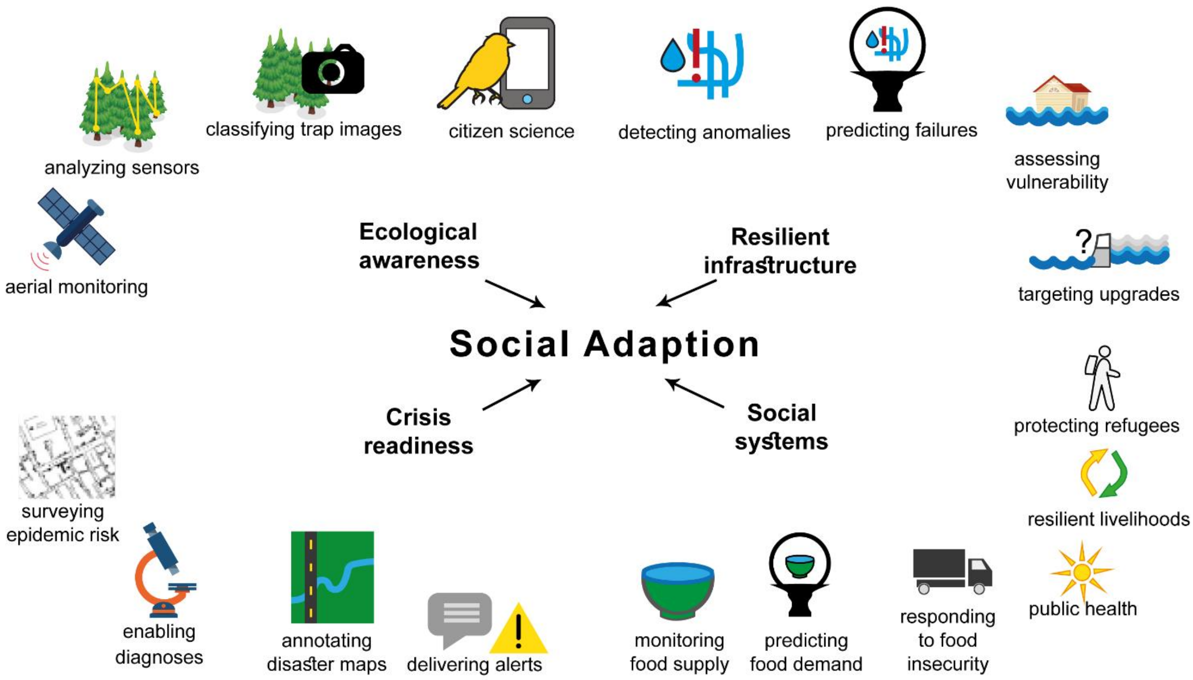

Figure 8. Systematic diagram of the opportunities of RAI in societal adaptation to climate change.

The prevalence and structure of ecosystems are progressively being affected by climate change. Global biodiversity, farming, illness, and environmental assets such as timber and fish are all affected by this. It is possible to use ML to aid in the monitoring of ecosystems and biodiversity. Protecting endangered species and halting the spread of the virus can be accomplished in tandem with biodiversity monitoring. With the help of machine learning, we can better analyze the effects of ecological actions and stop poaching before it happens. In our daily lives, physical infrastructure is so ingrained in our daily routines that it is easy to forget that it exists. Unsettling as it may be the necessity of fundamental rethinking can spur innovative thinking in the face of the looming challenge of climate change adaptation. There are two types of activities that can be supported by machine learning: design and maintenance. Physical infrastructure is vital, but so is the social infrastructure we build, and both need to be able to adapt to changing climate circumstances. To begin with, think about how these systems might be affected by modifications. Droughts in different continents have shown that crop yields are already declining, and this poses a threat to global food security. For populations that rely on ecological resources, this could lead to widespread migrations, as people seek more conducive locations. Algorithmic thought at first glance may not be able to solve these issues, but expenditures on social infrastructure can help [26-28].

4 | Conclusion

This work presents a theoretical framework to settle the pillars of RAI in a climate-in-mind manner aiming. The proposed framework considers multiple cutting-edge requirements such as interpretability, causality, greenness, trust, uncertainty, and security. Then, we chart out the road maps for applying responsible AI to mitigate and adapt to the challenges of climate change across different domains. The findings show that the battle against climate problems necessitates cooperation with fields within and outside computer science leading to interdisciplinary procedural novelties, such as enhanced physics-constrained ML techniques.

Acknowledgments

The author is grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

Author Contribution

All authors contributed equally to this work.

Funding

This research was supported by Korea Institute for Advancement of Technology (KIAT) grant funded by the Korea Gov-ernment(MOTIE) (P0012724, HRD Program for industrial Innovation) and the Soonchunhyang University Research Fund.

Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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