sustainability

Review

Assessing the Potential of AI–ML in Urban Climate Change Adaptation and Sustainable Development

Aman Srivastava and Rajib Maity *

Department of Civil Engineering, Indian Institute of Technology Kharagpur, Kharagpur 721302, India; amansrivastava1397@kgpian.iitkgp.ac.in
* Correspondence: rajib@civil.iitkgp.ac.in

Abstract: This study addresses a notable gap in the climate change literature by examining the potential of artificial intelligence and machine learning (AI–ML) in urban climate change adaptation and sustainable development across major global continents. While much attention has been given to mitigation strategies, this study uniquely delves into the AI–ML's underexplored role in catalyzing climate change adaptation in contemporary and future urban centers. The research thoroughly explores diverse case studies from Africa, Asia, Australasia, Europe, North America, and South America, utilizing a methodological framework involving six-step and five-step models for systematic literature reviews. The findings underscore AI–ML achievements, illuminate challenges, and emphasize the need for context-specific and collaborative approaches. The findings imply that a one-size-fits-all approach is insufficient. Instead, successful adaptation strategies must be intricately linked to the particular characteristics, vulnerabilities, and intricacies of each region. Furthermore, the research underscores the importance of international collaboration, knowledge sharing, and technology transfer to expedite the integration of AI–ML into climate adaptation strategies globally. The study envisions a promising trajectory for AI–ML in the climate adaptation domain, emphasizing the necessity for ongoing research, innovation, and practical AI–ML applications. As climate change remains a defining challenge, this research predicts an increasingly pivotal role for AI–ML in constructing climate-resilient urban centers and promoting sustainable development. Continuous efforts to advance AI–ML technologies, establish robust policy frameworks, and ensure universal access are crucial for harnessing AI–ML's transformative capabilities to combat climate change consequences.

Keywords: climate change consequences; climate resilience; sustainable urban development; AI–ML technology transfer; collaborative climate adaptation efforts; policy frameworks

check for updates

Citation: Srivastava, A.; Maity, R. Assessing the Potential of AI–ML in Urban Climate Change Adaptation and Sustainable Development. *Sustainability* **2023**, *15*, 16461. https://doi.org/10.3390/su152316461

Academic Editor: Andrzej Walega

Received: 25 October 2023
Revised: 21 November 2023
Accepted: 27 November 2023
Published: 30 November 2023

1. Introduction

Climate change, unequivocally recognized as one of the paramount challenges of the 21st century, has profound implications for the sustainability and resilience of urban centers worldwide [1,2]. Climate change, driven by human activities, poses unprecedented threats to Earth, with rising temperatures, extreme weather events, and sea-level rise being stark manifestations. Simultaneously, urbanization is rising, with most of the global population residing in cities. This urban expansion alters local climates, placing urban centers at the frontline of climate impacts [1,2]. In this context, sustainable development emerges as the imperative solution, seeking to harmonize environmental protection, economic growth, and social equity. Combating climate change and fostering urban sustainability are increasingly intertwined goals [3–5]. Climate scientists employ diverse methods to assess climate change. This includes complex climate models that project future scenarios, historical data analysis to identify trends, field studies to collect local data, proxy data for past climate reconstructions, remote sensing via satellites, statistical analysis for trend identification, impact assessments across sectors, emission inventories to track greenhouse gases, ocean and atmospheric measurements, and dedicated climate observatories. These traditional techniques and advanced AI–ML methods are foundational in understanding climate change [1,2]. Adopting advanced technologies, particularly AI–ML, offers a promising avenue to address this convergence, enabling informed decisions, resilient urban planning, and resource optimization to pursue a sustainable, climate-resilient future.

The exploration of AI–ML techniques is essential, more specifically for urban climate change adaptation and sustainable development, due to several compelling reasons that set it apart from traditional methods, as highlighted by Alanzi [6], Taghikhah et al. [7], Leal Filho et al. [8], Elbeltagi et al. [9], and Kumar et al. [10]. Firstly, urban environments present intricate and multifaceted climate challenges that demand the capability to handle complex and diverse datasets. AI–ML excels in this regard, enabling the unraveling of intricate relationships between urban development and climate change that traditional techniques often struggle with. Secondly, AI–ML provides predictive capabilities critical for urban planners and policymakers. It allows anticipation of climate-related events such as extreme weather patterns and sea-level rise, offering insights vital for urban resilience. Furthermore, the real-time data processing prowess of AI–ML is invaluable for urban areas where rapid adaptation can mitigate climate change impacts. This real-time adaptability surpasses traditional methods' often slower and less adaptable nature. AI–ML's adaptability extends to customization, ensuring that climate adaptation strategies are tailored to individual urban areas' unique characteristics and challenges, a level of specificity that generic methods often lack. Additionally, AI–ML optimizes resource allocation in various areas, from energy management to disaster response, leading to more efficient and cost-effective climate adaptation strategies. AI–ML also handles big data, a feature crucial for urban climate change research, as cities generate vast volumes of data from sources like sensors, satellites, and social media. Moreover, AI–ML encourages interdisciplinary collaboration by integrating data from various fields, such as meteorology, ecology, and urban planning. This fosters a holistic understanding of the complex interplay between climate and urban development. Lastly, the continuous learning ability of AI–ML is vital in the context of climate change, where conditions evolve over time. AI–ML models can adapt and enhance their accuracy as they encounter new data, ensuring that adaptation strategies remain up-to-date and effective [6–12]. These advantages collectively position AI–ML as a pivotal tool in addressing the challenges posed by climate change in urban areas, making it the method of choice for this study.

As the present understanding of climate science has evolved, extensive research efforts have been dedicated to developing and implementing mitigation strategies to curb greenhouse gas emissions (see Figure 1). Kaack et al. [13] presented a structured framework to describe the impact of ML on greenhouse gas (GHG) emissions. They could identify crucial areas for assessing impact and provide an understanding of how ML influences climate change mitigation. Sain et al. [14] explored the issues related to climate change and the utilization of fossil fuels and their effects on energy and water security. Plausible measures for mitigation and specific associated challenges were also highlighted, with a particular focus on Himalayan geo-hazards. Similarly, Sahil et al. [15] expounded on the significance of AI in mitigating climate change and its potential to play a vital role in accomplishing the Sustainable Development Goal (SDG) "Climate Action". Kaginalkar et al. [16] provided a perspective on the opportunity to tackle urban air quality management in the face of air pollution and climate change. The potential of integrated technologies, including the Internet of Things (IoT), big data, AI, smartphones, and social and cloud computing, was emphasized for enabling data-driven, strategic, and real-time actions in governance for mitigation and assisting citizens in making well-informed decisions. In general, all of these aforementioned studies exhaustively explored the potential of AL-ML in mitigating climate change consequences. However, amid this fervent discourse on mitigation, a conspicuous lacuna persists concerning the underexplored frontier of AI–ML as potent tools for catalyzing climate change adaptation within the intricate fabric of urban landscapes [8,17,18]. This is further demonstrated in Figure 1. The manuscript thus addresses this critical knowledge gap by embarking on an in-depth exploration of the multifaceted potential of AI–ML in the realm of urban climate change adaptation and sustainable development.

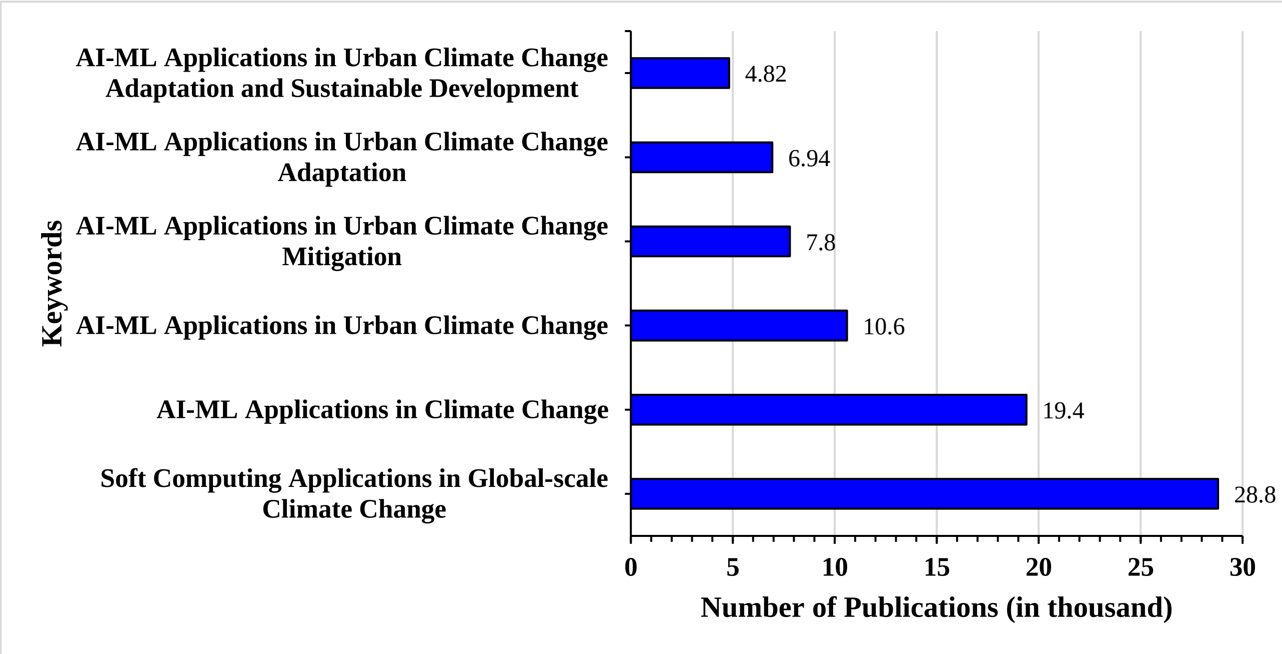

Figure 1. Summary of the published research on the keywords related to "Assessing the Potential of AI–ML in Urban Climate Change Adaptation and Sustainable Development" (Source: Google Scholar, accessed on 13 November 2023).

The lack of attention to adaptation-based approaches using AI–ML methods can be attributed to several factors. Firstly, the focus on climate change research has historically leaned heavily towards mitigation, as the urgency to reduce greenhouse gas emissions and curb the causes of climate change has been a primary concern. This emphasis on mitigation strategies has overshadowed the exploration of adaptation-based approaches, leaving a noticeable gap in the literature. Additionally, the complexity of climate adaptation presents unique challenges that may have deterred researchers. Adaptation strategies often need to be context-specific, considering different regions' diverse environmental, social, and economic conditions [19]. This complexity might have dissuaded some researchers from delving into the application of AI–ML, which demands a nuanced understanding of these intricacies. Moreover, another reason is the relatively recent recognition of the importance of adaptation in climate change resilience. Mitigation efforts have traditionally received more attention, and it is only in recent years, that the significance of adaptation, particularly in urban contexts, has gained prominence. In summary, a combination of historical research priorities, the complexity of adaptation, and a more recent acknowledgment of its importance have resulted in a dearth of attention to adaptation-based approaches using AI–ML methods in the existing literature. This article thus addresses a significant gap in the existing literature concerning the application of AI–ML in the context of adaptation and sustainable development. The study's objective is to evaluate the potential of AI–ML as a catalyst for climate change adaptation in both current and future urban centers. To achieve this objective, the investigation provides a comprehensive overview of how AI–ML can enhance cities' capacity to adapt to climate change. The article delves into distinct case studies that showcase various communities and organizations' utilization of AI–ML to support their adaptation efforts. These case studies span diverse geographic regions, including Africa, Asia, Australasia, Europe, North America, and South America. Throughout these case studies, the article highlights the successes and potentials of AI–ML and meticulously delineates the limitations and challenges that must be addressed. By rigorously examining these aspects, the study contributes valuable insights into the nuanced dynamics of implementing AI–ML solutions for climate adaptation. In conclusion, the study synthesizes the findings from the diverse case studies to derive overarching lessons. It emphasizes the importance of context-specific approaches and collaborative efforts in harnessing the full potential of AI–ML for climate adaptation. Furthermore, the article ponders the future trajectories of AI–ML in this realm, underlining the avenues for further research, innovation, and impactful application.

2. Methodology

This study has adopted six-step and five-step models for conducting systematic literature reviews, as described by Machi & McEvoy [20] and García-Granero et al. [21] and summarized in Table 1. The six-step model guides the systematic literature review process: Firstly, the process commences with selecting a well-defined research topic or question and setting the boundaries for the review. Secondly, comprehensive information gathering involves systematic searches across various databases, libraries, and other pertinent sources. Thirdly, a critical evaluation of the literature occurs. This phase entails assessing the quality and relevance of the amassed materials, typically involving screening and selecting studies according to predefined criteria. Subsequently, the selected studies undergo systematic data analysis and synthesis to uncover trends, patterns, or key findings. Following the synthesis, the process proceeds to conclude. In this step, the reviewer formulates conclusions based on the synthesized information and aligns them with the initial research question or objectives. Ultimately, the findings are reported in a structured manner, documenting the review's search methods, outcomes, and conclusions, thereby providing a comprehensive account of the systematic literature review. Additionally, the five-step model provides a structured framework for conducting a systematic literature review: To begin, the process starts with problem formulation, where the research problem or question is defined, thereby establishing the boundaries and focus of the review. Following this, the literature search phase unfolds, requiring a comprehensive and systematic search to identify pertinent literature sources. Subsequently, the model guides through the data collection and analysis step. Here, data are gathered from the selected sources (Scopus and Google Scholar for the present case) and rigorously analyzed to uncover patterns, themes, or trends within the literature. As the review progresses, the synthesis and discussion steps come into play. During this phase, the findings from the literature, discussions on key themes, and similarities and emerging differences are summarized and synthesized. Finally, the model concludes by drawing conclusions and providing recommendations. Based on the synthesized literature, the study formulates conclusions and offers valuable recommendations or implications for future research or practical applications in the field. Thus, these structured approaches ensure a methodical and comprehensive systematic literature review process [20,21].

Table 1. Methodological flow and criteria for evaluation of AI–ML in advancing climate change adaptation and sustainable development.

Approaches	Description
	Problem Formulation
Research Problem Definition:	The manuscript begins by clearly defining the research problem, which is the application of AI–ML in urban climate change adaptation.
Scope Clarification:	The scope of the study is articulated, focusing on both current and future urban centers across different regions of the world.

Table 1. *Cont.*

Approaches	Description
Literature Search:	
Comprehensive Searches:	A systematic and thorough literature search encompasses databases, libraries, and other relevant sources to ensure a comprehensive collection of existing literature.
Inclusivity:	The literature search includes various geographical regions, including Africa, Asia, Australasia, Europe, North America, South America, Small Islands, and Polar Regions.
Data Collection and Analysis:	
Data Gathering:	The manuscript gathers data from selected case studies that illustrate the utilization of AI–ML in climate adaptation. These case studies represent diverse geographic regions and urban characteristics.
Data Parameters:	Specific data parameters are considered during the analysis, including successes (positive outcomes and achievements), limitations (constraints and challenges faced), and challenges (obstacles that must be overcome) related to the use of AI–ML for climate adaptation.
Geographic Specifics:	Geographic specifics such as the region, urban setting, and environmental context are considered during the analysis to understand the variations and context-specific factors influencing AI–ML applications.
Synthesis and Discussion:	
Key Themes:	The study synthesizes key themes and patterns from the case studies, highlighting the contributions, innovations, and impacts of AI–ML in climate adaptation.
Similarities and Differences:	The manuscript explores the similarities and differences across the selected case studies to provide a nuanced understanding of AI–ML applications in different regions and urban contexts.
Contextual Factors:	Contextual factors, including geographical, urban, and environmental considerations, are discussed to shed light on the specific conditions influencing the successes or challenges of AI–ML in climate adaptation.
Conclusions and Recommendations:	
Conclusions:	The manuscript draws comprehensive conclusions based on the synthesized information, emphasizing AI–ML as a potent catalyst for climate change adaptation in urban settings.
Recommendations:	Recommendations are provided, emphasizing the importance of context-specific approaches tailored to different regions and the significance of collaborative efforts in harnessing the full potential of AI–ML for climate adaptation.
Future Trajectories:	The study explores the future trajectories of AI–ML in urban climate adaptation, underlining potential avenues for further research, innovation, and practical applications.

In the present research, both the six-step and the five-step methodological frameworks are used, devising a robust structure for investigating the role of AI–ML in climate change adaptation within urban environments (see Figure 2). Following the six-step model, the study began by precisely defining the research problem, addressing the critical gap in the existing literature regarding the application of AI–ML in climate change adaptation. This initial step established the research's scope and focus. Subsequently, a comprehensive literature search was conducted, aligning with the model's second step, to identify and gather relevant sources systematically. This phase involved exhaustive searches across databases, libraries, and other sources to ensure inclusivity. As per the five-step model, the research study transitioned to the data collection and analysis phase, drawing data from carefully selected sources. This stage facilitated the identification of patterns, trends, and key findings within the literature. Moving forward, the synthesis and discussion step allowed for the summarization and synthesis of findings, fostering discussions on significant themes and disparities. By integrating these two models, the study meticulously evaluated distinct case studies spanning diverse geographic regions, illustrating the application of AI–ML in climate change adaptation. It highlighted successful implementations and critically assessed limitations and challenges, aligning with the six-step model's emphasis on assessing the quality and relevance of gathered literature. Ultimately, this research synthesis enabled the drawing of comprehensive conclusions about the potential of AI–ML as a catalyst for climate change adaptation in urban centers. The study stressed the significance of context-specific approaches and collaborative efforts, aligning with the five-step model's emphasis on offering recommendations and implications for future research and practice. In conclusion, the systematic application of these models ensured the study's scientific rigor. It contributed valuable insights into the complex dynamics of implementing AI–ML solutions for climate adaptation, underlining the avenues for future research and impactful applications in urban sustainability. These detailed considerations align with the systematic and rigorous approach used in this investigation to assess the potential of AI–ML in urban climate change adaptation and sustainable development (see Table 1 and Figure 2).

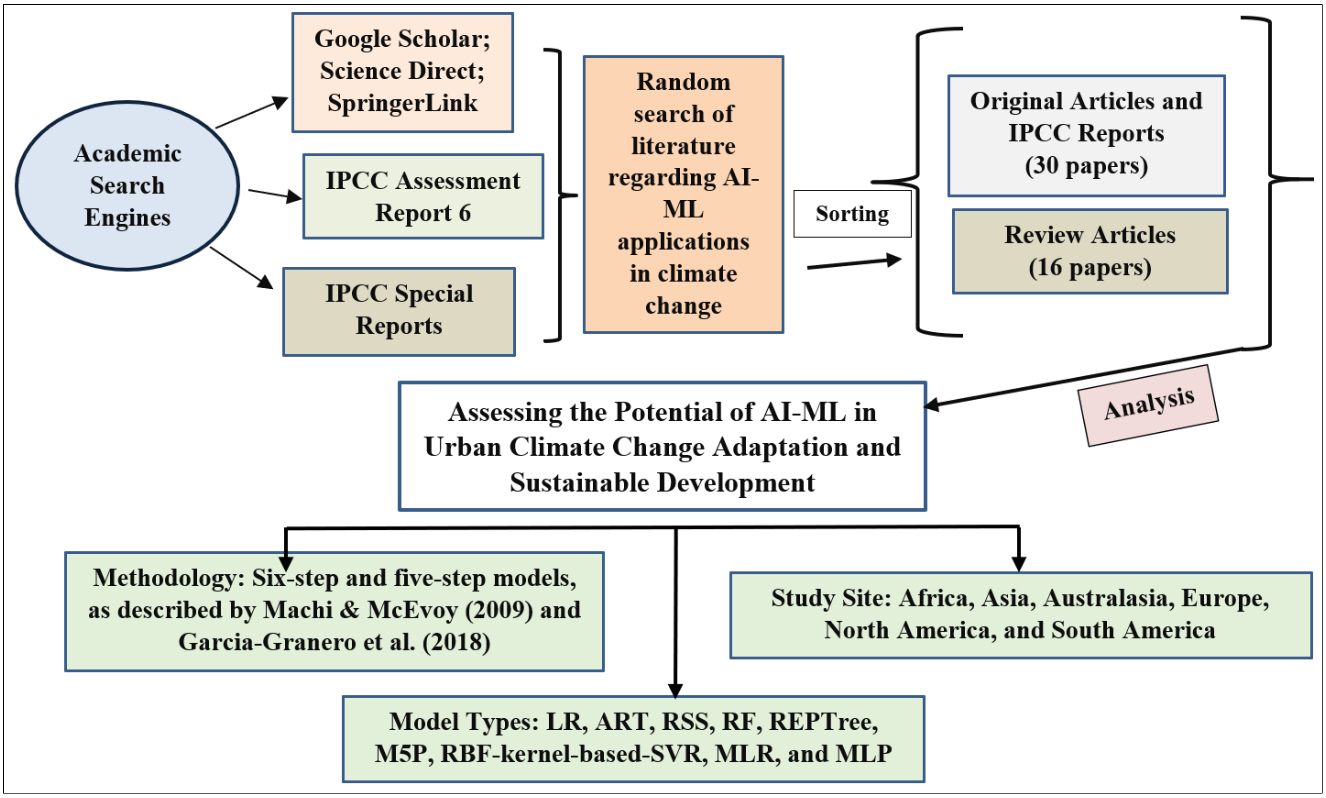

Figure 2. Flow diagram of the procedure for review of the literature regarding "Assessing the Potential of AI–ML in Urban Climate Change Adaptation and Sustainable Development" (Sources for methods adopted for methodology, as shown, include—Machi & McEvoy [20] and Garcia-Granero et al. [21]).

3. Case Studies of AI–ML in Climate Change Adaptation—Global Perspective

3.1. Africa

The African continent holds immense significance in climate change impact, risk, and adaptation studies. Its vulnerability to climate change is heightened due to its socioeconomic structure, which relies heavily on agriculture and natural resources. From savannas to rainforests, diverse ecosystems harbor unique biodiversity and provide vital ecosystem services. Additionally, Africa's geographical diversity offers a microcosm of climate variability, making it a valuable laboratory for studying climate change's diverse impacts. Comprehensive research informs global climate models, and guides targeted adaptation and mitigation strategies crucial for a sustainable future [8,22–24]. These are also supported by the IPCC [1,2]. Rapid population growth, existing food security, and water scarcity challenges underscore the urgency of understanding the role of AI–ML applications in climate change adaptations.

In the context of climate change adaptation in Africa, one compelling case study from Egypt will be assessed here to illuminate the transformative potential of AI–ML technologies. Elbeltagi et al. [9] offer valuable insights into the precise estimation of evapotranspiration (ET), a critical factor for effective agricultural water management in water-stressed developing countries amidst climate change (see Figure 3). Specifically, the case study focuses on forecasting vapor pressure deficit (VPD), a key parameter influencing ET calculation. The study encompasses eight distinct regions within Egypt, namely Dakahliyah, Gharbiyah, Kafr Elsheikh, Dumyat, Port Said, Ismailia, Sharqiyah, and Qalubiyah, each facing unique climatic challenges. To tackle this complex task, six ML algorithms were employed: linear regression (LR), additive regression trees (ART), random subspace (RSS), random forest (RF), reduced error pruning tree (REPTree), and Quinlan's M5 algorithm (M5P). The random forest (RF) model emerged as the frontrunner, exhibiting exceptional performance during the training and testing. Its impressive statistics, including a high correlation coefficient (CC = 0.9694), low error rates (mean absolute error (MAE) = 0.0967 and root mean square error (RMSE) = 0.1252), and relative error percentages (relative absolute error (RAE) = 21.7297 and root relative squared error (RRSE) = 24.0356), demonstrated its robustness in VPD forecasting. The study's findings highlight the RF model as a powerful tool for hydro-climatological studies and the modeling of VPD in Egypt and in analogous African urban environments. The study's predictive capabilities enable future climate magnitudes to be anticipated, providing a valuable resource for authorities and policymakers as they navigate specific pathways toward climate adaptation in urban centers across the continent.

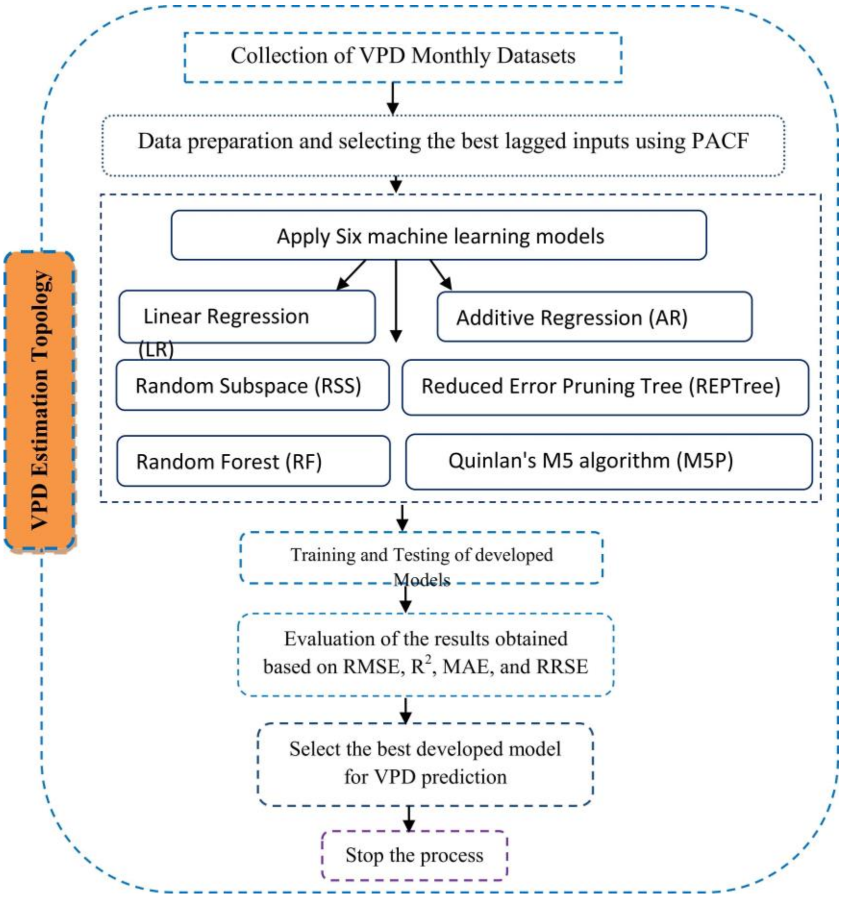

Figure 3. Flowchart of VPD estimation methodology for "Forecasting vapor pressure deficit for agricultural water management using machine learning in semi-arid environments" (adapted from Elbeltagi et al. [9]).

3.2. Asia

The Asian continent plays a pivotal role in climate change impact, risk, and adaptation studies for several compelling reasons. Its remarkable diversity encompasses many ecosystems, making it a microcosm of global climate change effects. The vast population relying heavily on agriculture underscores the importance of understanding how changing climate alters food security and water resources. Rapid urbanization and economic growth make Asian cities particularly vulnerable to climate-related challenges. Coastal communities face rising sea levels and extreme weather events. Additionally, Asia's role in the global carbon cycle and its growing economies emphasize the need to investigate how climate change affects ecosystems and carbon sequestration. Comprehensive research here informs global climate knowledge and guides targeted strategies for mitigation and adaptation, ensuring a sustainable future for Asia and the world [25–30]. These are also supported by IPCC [1,2]. Exploring the applications of AI–ML might be a way forward in devising climate change adaptation measures.

In assessing the potential of AI–ML in urban climate change adaptation and sustainable development, Kumar et al. [10] examined a groundbreaking case study to determine the interlinkages between changing climate and vector-borne disease in South Asia, particularly Bihar, a state in northern India (see Figure 4). This case study addressed the critical issue of *Visceral leishmaniasis* or Kala-azar (KA), a vector-borne disease with a high mortality rate, making it one of the deadliest parasitic diseases globally. South Asia, with India at its core, bears the brunt of KA cases, with Bihar alone accounting for over half of the Indian cases. Climate change vulnerabilities have been suspected as a driving force behind KA outbreaks, necessitating the development of effective epidemic prediction systems that can account for changing climate impacts. Coherently, a radial basis function (RBF) kernel-based support vector regression (SVR) model, termed RBF-kernel-based-SVR, was developed for the most affected endemic districts of Bihar. The results unveiled that temperature, wind speed, rainfall, and population density significantly contributed to KA outbreaks, underscoring the influence of climatic factors on disease dynamics. Multiple linear regression (MLR) and multilayer perceptron (MLP) models were also developed and compared with the RBF-kernel-based-SVR model to provide a comprehensive perspective. Encouragingly, the RBF-kernel-based-SVR model demonstrated superior performance, exhibiting a high correlation coefficient (CC = 0.82), low root-mean-square error (RMSE = 12.20), and a robust Nash–Sutcliffe efficiency (NSE = 0.66). This study's implications are far-reaching, recommending using the RBF-kernel-based-SVR model as a swift and efficient tool for detecting KA cases, particularly in regions with limited data availability. Such AI–ML models are promising for public health authorities to monitor KA spread, comprehend the climate impacts on outbreaks, and ensure timely and effective healthcare services in urban settings.

3.3. Australasia

With its extraordinary ecological diversity, Australasia is a critical focal point for climate change impact, risk, and adaptation studies. Its unique mix of ecosystems, from tropical rainforests to arid deserts, provides invaluable insights into climate change effects on diverse landscapes. Coastal communities face growing vulnerabilities due to rising sea levels and extreme weather events. Australasia's pivotal role in the global carbon cycle through vast forests necessitates researching how climate change affects carbon sequestration. Moreover, the region's growing population and urbanization highlight the urgency of understanding climate impacts on cities [29,31,32]. These are also supported by the IPCC [1,2]. There is a need to acquire global climate knowledge and inform targeted strategies for mitigation and adaptation, securing a sustainable future for Australasia and beyond in the context of AI–ML-based approaches.

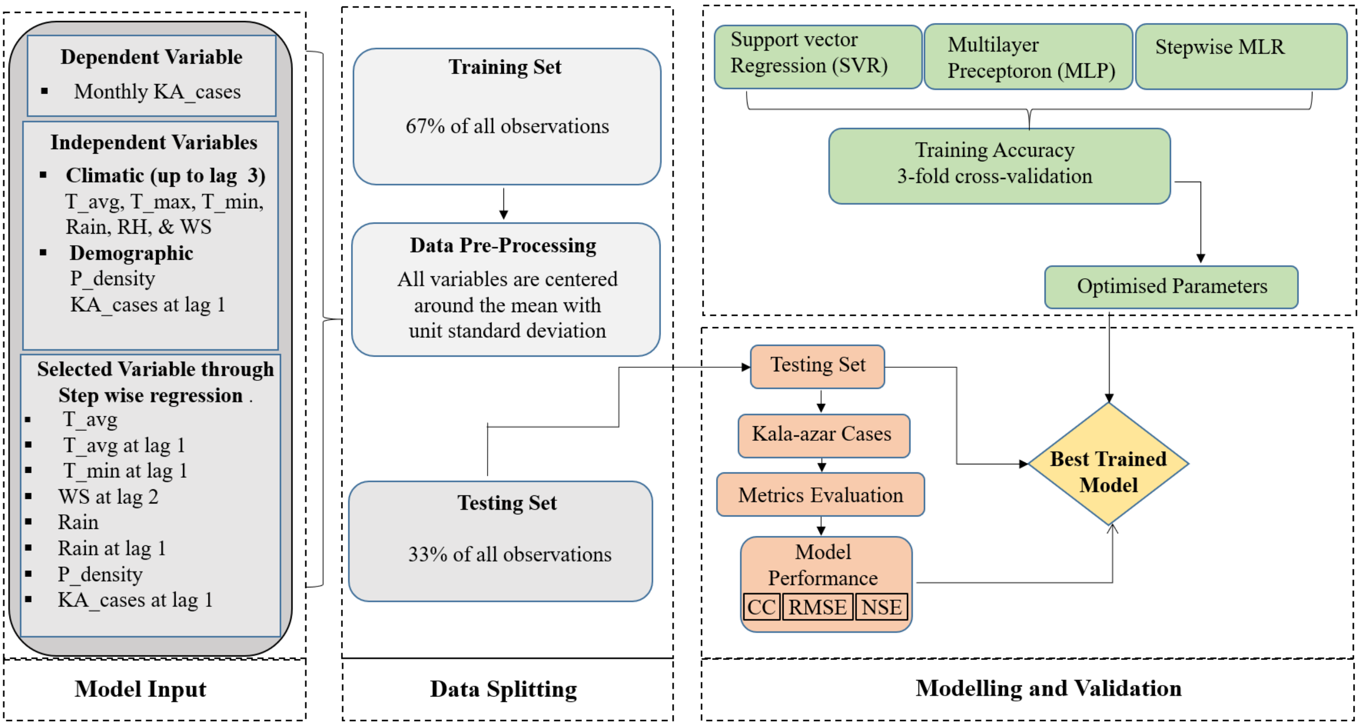

Figure 4. Methodological flowchart for "Modeling climate change impacts on vector-borne disease using machine learning models: Case study of *Visceral leishmaniasis* (Kala-azar) from Indian state of Bihar" (adapted from Kumar et al. [10]).

In the Australasian context, where wildfires are intrinsic components of ecosystems and hold profound significance in indigenous lore, the dynamic challenges posed by climate change have mandated a thorough reassessment of conventional wildfire management methodologies. Taghikhah et al. [7] undertake an exhaustive review to scrutinize the paradigm-shifting potential of AI–ML in confronting these evolving predicaments. Notably, AI's engagement in bushfire management, dating back to the 1990s with the inception of neural networks and expert systems, has laid the groundwork for remarkable progress. The integration of cutting-edge satellite technologies, exemplified by NASA's TERRA, AQUA, and GOES, has amplified wildfire surveillance capabilities. AI's contributions to weather forecasting and climate modeling have also refined fire weather predictions to unprecedented accuracy. The widescale adoption of a data-centric framework, characterized by machine learning models, is now standard practice within contemporary bushfire management. The spectrum of AI–ML applications in Australasia includes predictive modeling, encompassing the assessment and cartography of bushfire vulnerability, thus affording the latitude for proactive fire management strategies. Furthermore, AI is pivotal in formulating efficacious fuel treatment systems, guided by identifying variables with robust associations to wildfires, including environmental and socioeconomic determinants. Moreover, AI–ML contributes to delineating spatial patterns in wildfire occurrences, facilitating location-specific management interventions. A couple of applications in this regard include (a) the "An Eye on Recovery" project, a collaboration between WWF-Australia and Conservation International, which uses sensor cameras to monitor wildlife recovery after wildfires. This initiative deploys 600 cameras in areas affected by severe bushfires, shedding light on post-fire animal repopulation; (b) a fire-prone area "Citizen Science App" driven by AI that offers rapid and accurate fire forecasting, aiding targeted interventions and enhancing community responses. These applications represent future directions for AI in environmental management and climate adaptation. Evidence synthesis leads to an unequivocal assertion: AI–ML is a transformative force in Australasian wildfire management. It manifests as a data-driven, prognostic paradigm uniquely poised to grapple with the escalating complexities precipitated by climate change. In the region's vanguard of sustainable urban development and climate adaptation endeavors, AI–ML proactively empowers governing bodies to safeguard lives, property, and the environment, aligning seamlessly with their objectives.

3.4. Europe

Europe's significance in climate change impact, risk, and adaptation studies is undeniable. It grapples with rising temperatures, shifting precipitation patterns, and increasingly extreme events. These challenges vary across the continent, affecting diverse ecosystems from the Arctic to the Mediterranean. The intricacies of these impacts necessitate comprehensive research. Europe's historical, cultural, and economic diversity further highlights the urgency of understanding climate change's ramifications. From coastal vulnerabilities to changes in agriculture and energy demands, Europe's experiences resonate globally. In-depth studies have contributed to a broader understanding of climate dynamics [29,33–35]; also supported by the IPCC [1,2]), thereby paving the way to design targeted mitigation and adaptation strategies by utilizing the benefits of AI–ML applications and guiding Europe toward a more sustainable and resilient future.

Integrating innovative technologies such as AI–ML offers a transformative approach to climate change adaptation. Given this, Alanzi [6] extensively examined the functionalities and effectiveness of mobile health apps during the COVID-19 pandemic. The study applied a lens similar to that of using AI–ML in climate change adaptation strategies across Asia, Europe, and North America. Alanzi [6] reviewed apps such as COVID Symptom Study and NHS COVID-19 from the United Kingdom; Mawid, Tabaud, Tawakkalna, and Sehha from Saudi Arabia; Aarogya Setu from India; TraceTogether from Singapore; COVID Safe from Australia; Immuni from Italy; and COVID Watch and PathCheck SafePlaces from the United States of America. Like mobile health apps that harnessed Bluetooth, GPS, AI, and ML to bolster remote healthcare delivery during the pandemic, AI–ML can enhance climate change adaptation efforts. In Alanzi's study [6], certain mobile health apps like Arogya Setu and PathCheck demonstrated the potential for comprehensive services by combining self-assessment, consultations, support, and information access in a single application. While mobile health apps primarily focused on contact tracing for COVID-19, AI–ML in climate change adaptation addresses challenges like environmental monitoring, extreme weather event prediction, and resource allocation. The absence of all-encompassing mobile health apps underscores the need for integrated solutions, mirroring the requirement for unified AI–ML applications that cater to the complex demands of climate adaptation. This transition towards integrated, multi-functional applications aligns with the evolution of technology's role in addressing pressing global challenges.

3.5. North and South America

North America's significance in climate change studies is multifaceted. It witnesses rising temperatures, shifting precipitation patterns, and intensifying heat extremes. These changes impact agriculture, water resources, and coastal communities. North America's diverse landscapes, from the Arctic to arid regions, provide valuable insights into climate change's varied effects. Its vast population and economic importance amplify the urgency for research. Furthermore, it plays a pivotal role in the global carbon cycle. Understanding these impacts is vital for informed decision-making, from urban planning to conservation efforts. Studying North America's climate change impacts is crucial for understanding global climate and developing effective mitigation and adaptation strategies [29,36–38]). These are also supported by the IPCC [1,2]. Hence, exploring AI–ML-based applications may open up new research areas when devising climate change adaptations.

South America is a crucial focal point for climate change impact studies. Its vast ecological diversity, ranging from the Amazon rainforest to arid regions, presents a microcosm of climate change effects. Understanding these impacts is vital for global climate predictions. Additionally, South America's population heavily relies on agriculture and natural resources, making it highly vulnerable to shifts in climate impact drivers. Investigating these changes is essential for food security and ecological health. Coastal communities face risks from sea-level rise and extreme weather events, demanding resilience strategies. South America's unique ecosystems, economic significance, and climate variability make it integral to global climate research and adaptation efforts [29,39–41]. These are also supported by the IPCC [1,2]. Hence, exploring the AI–ML applications in combating the negative influence of changing climate may yield new sustainable pathways.

Within the framework of assessing the potential of AI–ML in urban climate change adaptation and sustainable development, it is vital to draw upon the insights of the investigation by Leal Filho et al. [8]. Their extensive research centered on the synergy between AI and the broader domain of climate change research, specifically emphasizing AI's invaluable role in advancing climate change adaptation efforts. In exploring AI–ML's applications in climate adaptation, their comprehensive approach sheds light on the multifaceted ways AI can underpin climate change research in various regions and contribute significantly to enhancing climate change adaptation strategies. A striking revelation from their research underscores the enthusiastic embrace of decision trees (DTs) and AI as indispensable tools for fortifying climate change adaptation efforts, particularly in North America and South America. Their appealing results, reflected by the resounding agreement of 80% of North American and 75% of South American respondents, underscores these technologies' critical nature and frequent application. The success of these technologies in these continents is closely tied to the presence of robust infrastructure that facilitates their effective deployment. Conversely, a different narrative emerges in the context of African respondents, with some indicating limited use of DTs and AI within their climate adaptation arsenal. This comparatively subdued enthusiasm for harnessing DTs and AI in addressing climate change adaptation in Africa can be attributed to the deficiency of the essential infrastructure required to support the application of these technologies. Consequently, this divergence in technological adoption presents an opportunity for technology developers to provide additional support to African nations, thereby closing the technology gap and invigorating more comprehensive climate change adaptation endeavors.

4. Results and Discussion

This section follows the "Synthesis and Discussion" part of the methodological framework, as described in Table 1, for all of the case studies discussed for different continents and beyond.

4.1. Africa

Climate change adaptation presents a pressing challenge for urban environments across the African continent, as has been highlighted in varying studies [1,2,8,22–24]. In this context, the integration of AI–ML technologies offers transformative potential. This assessment delves into a compelling case study from Egypt, underscoring the broader implications for urban climate change adaptation and sustainable development across Africa. More specifically, the case study by Elbeltagi et al. [9] focuses on precise ET estimation, a critical factor for effective agricultural water management, particularly in water-stressed developing countries (see Table 2). The significance of this case study extends beyond Egypt and resonates with urban environments throughout Africa. It highlights the transformative potential of AI–ML technologies in addressing climate change adaptation and sustainable development challenges. The RF model's predictive capabilities offer a valuable resource for authorities and policymakers, enabling them to anticipate future climate patterns and navigate specific pathways toward climate adaptation in urban centers across the continent. Unique challenges and opportunities mark the African context of climate change adaptation. AI–ML technologies, as showcased in the Egyptian case study, hold promise for bolstering sustainable development and resilience in the face of climate change. This case study underscores the need for systematic application and further research on AI–ML in urban climate change adaptation across Africa, emphasizing the urgency of addressing climate challenges with innovation and precision.

Table 2. Characterization of climate change adaptation research using artificial intelligence (AI) and machine learning (ML) concepts.

Research	Study Site	Climate Disaster	Sector(s)	AI–ML Approaches	Applications and Benefits	Challenges to Overcome and Scope
Elbeltagi et al. [9]	Egypt, a transcontinental country under Africa and Asia	Irrigation water scarcity due to altering vapor pressure deficit	Agriculture	LR, ART, RSS, RF, REPTree, and M5P	The study demonstrated its potential for precise evapotranspiration estimation, which is crucial for agricultural water management in water-stressed regions, thereby highlighting AI–ML's benefit in aiding policy-makers in targeted climate adaptation efforts.	Vapor pressure deficit modeling faces critical challenges. Ensuring historical data access is essential, particularly in data-scarce regions. Selecting the right algorithm for specific applications demands careful consideration. Implementing these models into operational systems is complex but vital for maximizing AI–ML benefits.
Kumar et al. [10]	Muzaffarpur and Saran districts from India under South Asia	Kala-azar diseases outbreaks	Health	RBF-kernel-based-SVR, MLR, and MLP	Combining these approaches allowed for a comprehensive analysis of climate–disease relationships, ultimately benefiting disease prediction and public health decision-making.	Challenges in RBF-kernel-based-SVR: Model complexity, hyperparameter tuning, data scaling, data availability. MLR: Linearity, multicollinearity, outliers, overfitting. MLP: Model complexity, hyperparameter tuning, preprocessing, data quantity, resources, interpretability.

Table 2. *Cont.*

Research	Study Site	Climate Disaster	Sector(s)	AI–ML Approaches	Applications and Benefits	Challenges to Overcome and Scope
Taghikhah et al. [7]	Australia under Australasia	Catastrophic forest fires	Environment	An Eye on Recovery Project and Citizen Science App	Case studies demonstrate AI's policy influence and wildfire control. AI-driven models and fire prediction apps indicate future AI applications. User-centric design, regulations, ethics, literacy, and understanding interdependencies are essential for AI's influential sustainability role.	Leveraging AI for climate resilience presents diverse challenges, from ethical concerns to regulatory frameworks and user trust. Investigating the interplay of psychological, sociological, organizational, and economic factors, enhancing AI literacy, and promoting resource efficiency are key to harnessing AI's potential.
Alanzi [6]	Saudi Arabia, Singapore, and India under Asia; Italy and the UK under Europe; the USA under North America	COVID-19 outbreak and climate	Health	Mobile Apps on COVID-19 for Outbreak Control	This study examined the efficacy of free mobile health applications used during the COVID-19 outbreak in various countries. It identified key functionalities, such as contact tracing, self-assessment, and appointment booking, focusing on GPS and Bluetooth technology. Few apps integrated multiple features.	Challenges in this study encompass ensuring global relevance, dealing with data privacy and user experiences, navigating regulatory differences, addressing technical complexities, ensuring data security, accommodating cross-cultural diversity, and managing resource demands. These challenges are pivotal in effectively deploying integrated mobile health applications, supporting their potential in healthcare services.

Table 2. *Cont.*

Research	Study Site	Climate Disaster	Sector(s)	AI–ML Approaches	Applications and Benefits	Challenges to Overcome and Scope
Leal Filho et al. [8]	Asia, Europe, Australasia, and North America	Water mis-management (also in agriculture) and wildfire	Natural resources	AI in general and Digital Technologies (DTs) in specific	The study analyzes disparities, improves infrastructure, addresses privacy and risk concerns, supports education and research, enhances resilience, aids post-COVID-19 recovery, and ensures systematic deployment. It also fosters research for climate change mitigation, offering a comprehensive toolset for sustainable environmental management.	Regional disparities in AI adoption complicate achieving equitable application. Infrastructure gaps in less-developed regions hinder integration. Overcoming fears and resistance to AI is crucial, necessitating effective education. Implementing AI systematically across diverse regions with varying readiness levels is complex. Addressing these challenges is essential for effective and equitable AI–ML adaptation to climate change.

4.2. Asia

Urban centers across Asia face multifaceted challenges in adapting to the impacts of climate change, as has been highlighted in varying studies [1,2,25–30]. Like Africa, integrating AI–ML technologies can offer transformative potential in the Asian context. This assessment explores an enlightening case study from South Asia, specifically Bihar, India, shedding light on broader implications for urban climate change adaptation and sustainable development across the continent. The case study by Kumar et al. [10] delves into the critical issue of *Visceral leishmaniasis*, a deadly vector-borne disease (see Table 2). With a significant burden in India, particularly Bihar, South Asia faces the brunt of KA cases. This study sought to understand the interplay between changing climate patterns and the dynamics of vector-borne diseases, focusing on Bihar, India. The case study's findings have far-reaching implications for urban centers in Asia grappling with vector-borne diseases and the influence of climate change. The RBF-kernel-based-SVR model offers a swift and efficient tool for detecting KA cases, particularly in regions with limited data availability. This AI–ML model holds promise for public health authorities to monitor disease spread, understand the climate impacts on outbreaks, and ensure timely and effective healthcare services in urban settings. The case study from Bihar, India, exemplifies the transformative potential of AI–ML in addressing vector-borne diseases aggravated by climate change. Its implications extend beyond Bihar, offering a model for urban climate change adaptation and sustainable development across Asia. AI–ML technologies are vital in understanding complex climate–disease relationships and developing effective strategies for resilient urban centers in the face of climate change.

4.3. Australasia

Australasia's unique ecological makeup, where wildfires are intrinsic components of ecosystems and hold profound significance in indigenous lore, necessitates reevaluating traditional wildfire management and other climatic disasters in the face of climate change, as has been highlighted in varying studies [1,2,29,31,32]. Coherently, Taghikhah et al. [7] shed light on the transformative potential of AI–ML in addressing the evolving challenges of bushfire management. AI's involvement in bushfire management has laid the groundwork for remarkable progress in confronting wildfires. Contemporary bushfire management revolves around a data-centric framework characterized by machine learning models that have become standard practice. Thus, AI–ML is at the heart of proactive fire management strategies in Australasia. It is pivotal in predictive modeling for bushfire vulnerability assessment and cartography and delineating spatial patterns in wildfire occurrences, allowing for location-specific management interventions. The "An Eye on Recovery" project and "Citizen Science App" applications represent future directions for AI in environmental management and climate adaptation (see Table 2). Evidence synthesis underscores AI–ML as a transformative force in Australasian wildfire management. Moreover, AI–ML identifies and mitigates urban heat islands, enhances infrastructure resilience, and aids in emergency response and evacuation planning by analyzing historical and real-time weather data. It optimizes natural resource management, particularly in regions prone to water scarcity, and streamlines waste management and recycling efforts. AI–ML also plays a pivotal role in developing sustainable, low-emission innovative transportation systems while continuously monitoring urban air quality and providing alerts and recommendations during deteriorations. These nuanced applications demonstrate AI–ML's potential to address specific climate challenges, fostering more resilient and sustainable Australasian cities.

4.4. Europe

In the European context, AI–ML presents a transformative approach to urban climate change adaptation and sustainable development, as exemplified by Alanzi's [6] extensive study of mobile health apps during the COVID-19 pandemic and as underlined by other studies [1,2,29,33–35]. This analysis expands to consider AI–ML's remarkable potential in climate adaptation across Europe, Asia, and North America. The study scrutinized various mobile health apps rooted in AI and ML and demonstrated their capability to deliver comprehensive services, combining self-assessment, consultations, support, and information access. This experience underlines the pressing need for integrated AI–ML applications capable of addressing the multifaceted demands of climate adaptation. This European and other continental perspective underscores a transition towards integrated, multi-functional applications, echoing the evolving role of technology in tackling global challenges. In essence, the integration of AI–ML technology unveils transformative opportunities for climate adaptation, akin to its role in healthcare during the pandemic. The continent is at the forefront of urban sustainability and climate resilience, empowered by AI–ML's capacity to safeguard lives, property, and the environment in the face of climate change. Europe's strong commitment to sustainability and climate action, combined with the multifaceted applications of AI–ML, positions the region at the forefront of global climate change combat efforts. These technologies empower data-driven decision-making, resource allocation optimization, and environmental impact reduction, fostering more resilient, adaptive, and sustainable urban environments across the continent.

4.5. North and South America

Drawing on the insights from Leal Filho et al. [8] and others, the paramount role of AI–ML in urban climate change adaptation across North and South America is manifest [1,2,29,36–41]. Their extensive study elucidates how AI can act as a linchpin in climate change research and the fortification of adaptation strategies across diverse regions. Within this expansive landscape, DTs and AI emerge as pivotal instruments. Notably, the research showcases the fervent endorsement of these technologies in North and South America, where an impressive 80% and 75% of respondents, respectively, unequivocally acknowledge their indispensable status and frequent application. The prevailing success of DTs and AI in these continents is closely intertwined with robust infrastructure, which seamlessly facilitates their effective deployment, empowering urban centers to navigate the challenges posed by a changing climate. However, the narrative shifts when exploring the context of African respondents. A different tale unfolds, marked by the palpable restraint in embracing DTs and AI as integral components of their climate adaptation toolbox. This restrained application can primarily be ascribed to the insufficiency of the requisite infrastructure to utilize these transformative technologies fully. This divergence in technological adoption serves as a clarion call to technology developers, urging them to actively bridge the technology gap in African nations. Such efforts promise to invigorate more comprehensive climate change adaptation endeavors and nurture sustainable urban development more equitably and globally. In sum, this comprehensive analysis underscores the indispensable role of AI–ML as a catalyst for climate change adaptation in the urban landscapes of North and South America. It vividly exemplifies how these technologies, coupled with robust infrastructure, can empower regions to navigate the multifaceted challenges of climate change. However, it also serves as a poignant reminder of the pressing need for equitable access to these transformative tools globally, underlining the imperative for all nations to harness the potential of AI–ML in their journey toward sustainable urban development and climate resilience.

5. Lessons Learned and Future Potential

Lessons from AI–ML in African climate adaptation reveal the need for robust infrastructure, equitable tech access, localized solutions, capacity building, and international collaboration. A multi-sectoral approach is vital, and policy frameworks are essential for responsible AI–ML use. Quality data and data management are fundamental for model accuracy. AI–ML's future in tackling climate change in Africa is promising. Lessons learned suggest that African nations should focus on localized AI–ML solutions, partnerships, and capacity building. Infrastructure investment is essential, as is promoting data quality through sharing. Expanding AI–ML beyond climate adaptation to various sectors is wise, and robust policy and regulation are crucial. The potential for AI–ML in Africa is significant, offering a potent tool for climate resilience and sustainable urban development.

For the Asian continent, insights underscore the importance of tailoring AI–ML solutions to address the diverse climate challenges in Asia. Additionally, capacity building is vital to empower Asian nations with the skills needed for effective AI–ML implementation. Integrating AI–ML across health, agriculture, and disaster management sectors enhances resilience. Collaborative efforts and technology transfer can expedite AI–ML adoption, while robust policy frameworks ensure the responsible and effective use of AI–ML technologies. High-quality, accessible data are fundamental, and investment in data collection and management is crucial to enhance AI–ML accuracy. Furthermore, optimizing renewable energy integration through AI–ML can contribute to sustainable development. These strategies pave the way for a promising future in which AI–ML is a powerful tool in combatting climate change and building resilient urban centers across Asia.

Australasia has recognized the value of AI–ML in wildfire management. AI has significantly improved wildfire surveillance and prediction, enhancing fire weather forecasting and proactive fire management. The use of AI–ML for environmental monitoring, such as tracking wildlife recovery after wildfires and offering rapid and accurate fire forecasting, has been a successful approach. These applications highlight the potential for AI–ML to contribute to broader environmental management efforts. Furthermore, Australasia has leveraged AI–ML to engage citizens in climate adaptation. Initiatives like the "Citizen Science App" that offers rapid and accurate fire forecasting demonstrate the potential for technology to involve the public in climate adaptation and response efforts. Expanding AI–ML beyond wildfire management to areas like health, agriculture, and disaster management enhances resilience and sustainability. Developing comprehensive policy and regulatory frameworks addressing data privacy and ethics is essential to ensuring responsible AI–ML use. International collaboration offers knowledge exchange and resource pooling opportunities to accelerate AI–ML integration into climate adaptation. Continued investment in data collection and sharing improves data quality and model accuracy. Sustainable agriculture, aided by AI–ML, enhances food security and environmental sustainability. These strategies position Australasia for climate resilience and sustainable development in a changing climate.

The European continent has gleaned crucial lessons from applying AI–ML techniques in combating climate change consequences. These insights emphasize the significance of data-driven climate adaptation, enabling precise predictions of extreme weather events, sea-level rise, and temperature changes. Moreover, the effective use of AI–ML to identify and mitigate urban heat islands has been recognized, emphasizing strategies like increasing green spaces and optimizing building design. Energy efficiency is another critical facet, with smart grids and predictive models reducing carbon emissions. Sustainable transportation has been improved through AI–ML's traffic flow optimization and eco-friendly options promotion. Furthermore, AI–ML optimizes natural resource management, enhances waste management and recycling, and continuously monitors air quality for public health protection. Integration into renewable energy systems and cross-sectoral applications is the future scope, emphasizing the importance of robust policy frameworks, international collaboration, data management, sustainable agriculture, and improved natural disaster response. These lessons and prospects are pivotal in enhancing European climate resilience and sustainability.

Both North and South American continents recognize the value of AI–ML in climate change adaptation, particularly DTs and AI, as crucial tools for adaptation efforts. The success of AI–ML in these regions is closely tied to their robust technological infrastructure. However, this success highlights technology adoption disparities, as some regions, like parts of Africa, experience limited AI–ML adoption due to infrastructure deficiencies. This variation underscores the global need for equitable access to technology to effectively address climate change adaptation challenges. Looking ahead, North and South America's future scope involves expanding AI–ML applications to diverse sectors linked to climate change, including health, agriculture, and disaster management. To ensure responsible AI–ML use, comprehensive policy and regulatory frameworks are crucial, addressing data privacy, ethics, and standards. Collaboration with international organizations, data enhancement, and optimizing renewable energy integration complete the envisioned path toward enhanced climate resilience and sustainable development across the continents.

Small islands hold a distinct and critical position in climate change impact studies. They often serve as early indicators of global climate trends due to their vulnerability to rising sea levels, extreme weather events, and coastal erosion—moreover, small islands house unique ecosystems and biodiversity hotspots. Understanding how climate change affects these environments is crucial for conservation efforts. Lastly, these islands often face water scarcity and agricultural challenges, highlighting the need for adaptation strategies to secure livelihoods and ecosystems. Small islands play a pivotal role in advancing climate science and adaptation practices. Hence, studying the applications of AI–ML-based climate change adaptation approaches in these regions may provide insights into broader climate dynamics.

Polar regions are critical in climate change studies due to their unique responses to global warming. The Antarctic Peninsula's significant warming and the Arctic's rapid changes provide crucial data for climate modeling. These regions are early warning systems for the planet's broader climate shifts, like small islands. The melting polar ice contributes to rising sea levels, impacting global coastlines. Moreover, polar ecosystems store vast amounts of carbon, from ice sheets to permafrost. Understanding their vulnerability and carbon dynamics is vital for climate mitigation. Lastly, studying polar regions helps predict extreme weather patterns and informs adaptation strategies, making them indispensable for comprehensive climate research. Thus, AI–ML-based climate change adaptation approaches may be one of the approaches that can be explored for polar regions in the present context.

The findings collectively contribute to the understanding of AI–ML applications in diverse geographic contexts, offering insights into climate adaptation strategies, technology integration, and the importance of collaborative, region-specific approaches, as summarized below:

- In Africa, lessons underscore the necessity of robust infrastructure and equitable technology access for effective climate adaptation in Africa, emphasizing the importance of localized AI–ML solutions tailored to diverse climate challenges and the vital role of capacity building and international collaboration in empowering nations for effective AI–ML implementation.
- In Asia, tailoring AI–ML solutions to diverse climate challenges, crucial capacity building, and integration across sectors enhance resilience by empowering nations with the skills needed for effective AI–ML implementation.
- In Australasia, AI–ML is employed for comprehensive wildfire management, enhancing surveillance, prediction, and public engagement, extending to environmental monitoring and tracking wildlife recovery after wildfires, with initiatives like the "Citizen Science App" showcasing the potential for technology to engage the public in climate adaptation.
- In Europe, AI–ML supports data-driven climate adaptation, predicting extreme weather, addressing sea-level rise, and mitigating urban heat islands through strategies like green space. It also enhances energy efficiency with smart grids and predictive models, reducing carbon emissions and improving sustainable transportation.
- Success in North and South America with AI–ML is closely linked to robust technological infrastructure, underlining global disparities in technology adoption and emphasizing the importance of ensuring equitable access for effective climate change adaptation.
- Small islands, vulnerable and with unique ecosystems, serve as early indicators of global climate trends. Addressing water scarcity and agricultural challenges through AI–ML is crucial for securing livelihoods and ecosystems on these islands.
- Polar regions, crucial in climate change studies, provide essential data for climate modeling and monitoring. Understanding vulnerability and carbon dynamics in polar ecosystems contributes to climate mitigation strategies.

The lessons learned from the extensive exploration of AI–ML applications in urban climate change adaptation and sustainable development underscore the transformative potential of these technologies. Navigating the intricate challenges posed by climate change reveals that the development of AI and ML is pivotal in enhancing urban resilience and shaping the business models of key industry players. These can include diverse stakeholders, such as technology companies specializing in AI and ML solutions for climate resilience, environmental consulting firms, urban planning and development agencies, governmental bodies, and corporations involved in sustainable practices. Recognizing the symbiotic relationship between technological advancements and strategic business approaches is crucial for fostering a sustainable future. The analysis sheds light on the successes and potentials of AI–ML, providing a foundation for understanding the interplay between technology, industry dynamics, and climate resilience. Through continued innovation, collaboration, and strategic policy formulations, the full potential of AI–ML can be harnessed to build climate-resilient urban centers and foster sustainable development in the years to come.

6. Conclusions

In conclusion, this study has significantly contributed to addressing a crucial gap in existing climate change literature by exploring the potential of AI–ML in urban climate change adaptation and sustainable development across diverse continents. While mitigation strategies have garnered considerable attention, this research uniquely delves into the underexplored domain of leveraging AI–ML to catalyze climate change adaptation in both current and future urban centers. The exploration of case studies spanning Africa, Asia, Australasia, Europe, North America, and South America has shed light on the successes, potentials, limitations, and challenges of AI–ML applications. The study underscores the importance of context-specific approaches and collaborative efforts in fully harnessing the potential of AI–ML for climate adaptation. Successful AI–ML applications, as emphasized, are intricately linked to understanding the unique characteristics and challenges of individual regions. Moreover, the study highlights the imperatives of international collaboration, knowledge sharing, and technology transfer to expedite the global integration of AI–ML into climate adaptation strategies. Regarding the limitations, this study concentrated on the role of AI–ML in urban climate change adaptation, offering a comprehensive overview but lacking an in-depth exploration of specific AI–ML models or techniques, which could limit the technical analysis. There may be a potential geographic bias in the case studies and examples, as one case study was focused on each continent, potentially neglecting unique challenges and opportunities in less-represented areas of the same continent. This presents an avenue for future researchers to emphasize context-specific investigations coherently with the current study objectives.

Moving forward, the study envisions a trajectory for AI–ML in the climate adaptation domain and emphasizes the need for continued research, innovation, and impactful application of AI–ML techniques. Given that climate change remains a defining challenge, the study asserts that AI–ML will increasingly play a pivotal role in constructing climate-resilient urban centers and promoting sustainable development. Consequently, the study calls for sustained efforts to advance AI–ML technologies, establish robust policy frameworks, and ensure equitable access to these tools globally. This imperative not only harnesses the transformative power of AI–ML to confront the consequences of climate change but also lays the foundation for a more sustainable and resilient future for all. In light of these findings, policymakers are urged to consider the nuanced dynamics outlined in this study when formulating climate adaptation policies. The context-specific nature of successful AI–ML applications highlights the importance of tailoring strategies to the unique challenges faced by individual regions. Furthermore, the emphasis on international collaboration suggests that policymakers should actively engage in knowledge-sharing initiatives and support technology transfers to ensure the effective integration of AI–ML into climate adaptation efforts worldwide. The study's call for ongoing research and innovation underscores the need for policymakers to prioritize investments in AI–ML technologies and support initiatives that advance their application in climate adaptation. By doing so, policymakers can position their jurisdictions at the forefront of resilient and sustainable urban development in the face of climate change challenges.

Author Contributions: A.S.: Methodology; formal analysis; investigation; data curation; writing—original draft preparation; visualization. R.M.: Conceptualization; validation; resources; writing—review and editing; supervision; project administration; funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The study was partially supported by a project sponsored by the Space Application Center (SAC), Indian Space Research Organization (ISRO), Ahmedabad (Ref. No. IIT/KCSTC/Chair/NEW/P/19-20/09). The Research Scholar (Aman Srivastava) funding was supported by the Prime Minister's Research Fellowship (PMRF/2401746/21CE91R03) under the Ministry of Education, Government of India. Thanks to the Department of Civil Engineering, Indian Institute of Technology (IIT) Kharagpur, for providing open access to the research literature library for conducting the review.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. IPCC. *Climate Change 2021: The Physical Science Basis*; Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change; Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., et al., Eds.; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2021. [CrossRef]
2. IPCC. *Climate Change 2023: Synthesis Report*; Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change; Core Writing Team, Lee, H., Romero, J., Eds.; IPCC: Geneva, Switzerland, 2023; pp. 35–115. Available online: https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_FullVolume.pdf (accessed on 28 November 2023).
3. Kelman, I. Linking disaster risk reduction, climate change, and the sustainable development goals. *Disaster Prev. Manag. Int. J.* **2017**, *26*, 254–258. [CrossRef]
4. Reckien, D.; Creutzig, F.; Fernandez, B.; Lwasa, S.; Tovar-Restrepo, M.; Mcevoy, D.; Satterthwaite, D. Climate change, equity and the Sustainable Development Goals: An urban perspective. *Environ. Urban.* **2017**, *29*, 159–182. [CrossRef]
5. Toukabri, M.; Youssef, M.A.M. Climate change disclosure and sustainable development goals (SDGs) of the 2030 agenda: The moderating role of corporate governance. *J. Inf. Commun. Ethic Soc.* **2022**, *21*, 30–62. [CrossRef]
6. Alanzi, T. A review of mobile applications available in the app and Google Play stores used during the COVID-19 outbreak. *J. Multidiscip. Healthc.* **2021**, *14*, 45–57. [CrossRef] [PubMed]
7. Taghikhah, F.; Erfani, E.; Bakhshayeshi, I.; Tayari, S.; Karatopouzis, A.; Hanna, B. Artificial intelligence and sustainability: Solutions to social and environmental challenges. In *Artificial Intelligence and Data Science in Environmental Sensing*; Academic Press: Cambridge, MA, USA, 2022; pp. 93–108. [CrossRef]
8. Leal Filho, W.; Barbir, J.; Gwenzi, J.; Ayal, D.; Simpson, N.P.; Adeleke, L.; Tilahun, B.; Chirisa, I.; Gbedemah, S.F.; Nzengya, D.M.; et al. The role of indigenous knowledge in climate change adaptation in Africa. *Environ. Sci. Policy* **2022**, *136*, 250–260. [CrossRef]
9. Elbeltagi, A.; Srivastava, A.; Deng, J.; Li, Z.; Raza, A.; Khadke, L.; Yu, Z.; El-Rawy, M. Forecasting vapor pressure deficit for agricultural water management using machine learning in semi-arid environments. *Agric. Water Manag.* **2023**, *283*, 108302. [CrossRef]
10. Kumar, S.; Srivastava, A.; Maity, R. Modeling climate change impacts on vector-borne disease using machine learning models: Case study of *Visceral leishmaniasis* (Kala-azar) from Indian state of Bihar. *Expert Syst. Appl.* **2024**, *237*, 121490. [CrossRef]
11. Liu, Y.; Yan, Z.; Tan, J.; Li, Y. Multi-Purpose Oriented Single Nighttime Image Haze Removal Based on Unified Variational Retinex Model. *IEEE Trans. Circuits Syst. Video Technol.* **2022**, *33*, 1643–1657. [CrossRef]
12. Zhang, S.; Zhang, X.; Wan, S.; Ren, W.; Zhao, L.; Shen, L. Generative Adversarial and Self-Supervised Dehazing Network. *IEEE Trans. Ind. Inform.* **2023**. [CrossRef]
13. Kaack, L.H.; Donti, P.L.; Strubell, E.; Kamiya, G.; Creutzig, F.; Rolnick, D. Aligning artificial intelligence with climate change mitigation. *Nat. Clim. Chang.* **2022**, *12*, 518–527. [CrossRef]
14. Sain, K. Climate Change and Fossil Fuels: Impacts, Challenges and Plausible Mitigation. *J. Geol. Soc. India* **2023**, *99*, 454–458. [CrossRef]
15. Sahil, K.; Mehta, P.; Bhardwaj, S.K.; Dhaliwal, L.K. Development of mitigation strategies for the climate change using artificial intelligence to attain sustainability. In *Visualization Techniques for Climate Change with Machine Learning and Artificial Intelligence*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 421–448. [CrossRef]
16. Kaginalkar, A.; Kumar, S.; Gargava, P.; Niyogi, D. Review of urban computing in air quality management as smart city service: An integrated IoT, AI, and cloud technology perspective. *Urban Clim.* **2021**, *39*, 100972. [CrossRef]
17. Balogun, A.-L.; Marks, D.; Sharma, R.; Shekhar, H.; Balmes, C.; Maheng, D.; Arshad, A.; Salehi, P. Assessing the Potentials of Digitalization as a Tool for Climate Change Adaptation and Sustainable Development in Urban Centres. *Sustain. Cities Soc.* **2020**, *53*, 101888. [CrossRef]
18. Sirmacek, B.; Vinuesa, R. Remote sensing and AI for building climate adaptation applications. *Results Eng.* **2022**, *15*, 100524. [CrossRef]
19. Srivastava, A.; Maity, R. Unveiling an Environmental Drought Index and its applicability in the perspective of drought recognition amidst climate change. *J. Hydrol.* **2023**, *627*, 130462. [CrossRef]
20. Machi, L.A.; McEvoy, B.T. *The Literature Review: Six Steps to Success*; Corwin Press: Thousand Oaks, CA, USA, 2009.
21. García-Granero, E.M.; Piedra-Muñoz, L.; Galdeano-Gómez, E. Eco-innovation measurement: A review of firm performance indicators. *J. Clean. Prod.* **2018**, *191*, 304–317. [CrossRef]
22. Lawal, S.; Lennard, C.; Hewitson, B. Response of southern African vegetation to climate change at 1.5 and 2.0° global warming above the pre-industrial level. *Clim. Serv.* **2019**, *16*, 100134. [CrossRef]
23. Parkes, B.; Cronin, J.; Dessens, O.; Sultan, B. Climate change in Africa: Costs of mitigating heat stress. *Clim. Chang.* **2019**, *154*, 461–476. [CrossRef]
24. Ofori, S.A.; Cobbina, S.J.; Obiri, S. Climate Change, Land, Water, and Food Security: Perspectives from Sub-Saharan Africa. *Front. Sustain. Food Syst.* **2021**, *5*, 680924. [CrossRef]
25. Zhu, J.; Poulsen, C.J.; Otto-Bliesner, B.L. High climate sensitivity in CMIP6 model not supported by paleoclimate. *Nat. Clim. Chang.* **2020**, *10*, 378–379. [CrossRef]

26. Rana, A.; Nikulin, G.; Kjellström, E.; Strandberg, G.; Kupiainen, M.; Hansson, U.; Kolax, M. Contrasting regional and global climate simulations over South Asia. *Clim. Dyn.* **2020**, *54*, 2883–2901. [CrossRef]
27. Ma, X.; Zhu, J.; Yan, W.; Zhao, C. Projections of desertification trends in Central Asia under global warming scenarios. *Sci. Total Environ.* **2021**, *781*, 146777. [CrossRef]
28. Wang, Z.; Lin, L.; Xu, Y.; Che, H.; Zhang, X.; Zhang, H.; Dong, W.; Wang, C.; Gui, K.; Xie, B. Incorrect Asian aerosols affecting the attribution and projection of regional climate change in CMIP6 models. *NPJ Clim. Atmos. Sci.* **2021**, *4*, 2. [CrossRef]
29. Zhou, T. New physical science behind climate change: What does IPCC AR6 tell us? *Innovation* **2021**, *2*, 100173. [CrossRef]
30. Elbeltagi, A.; Srivastava, A.; Li, P.; Jiang, J.; Jinsong, D.; Rajput, J.; Khadke, L.; Awad, A. Forecasting actual evapotranspiration without climate data based on stacked integration of DNN and meta-heuristic models across China from 1958 to 2021. *J. Environ. Manag.* **2023**, *345*, 118697. [CrossRef]
31. Ji, F.; Evans, J.P.; Di Virgilio, G.; Nishant, N.; Di Luca, A.; Herold, N.; Downes, S.M.; Tam, E.; Beyer, K. Projected changes in vertical temperature profiles for Australasia. *Clim. Dyn.* **2020**, *55*, 2453–2468. [CrossRef]
32. Howard, E.; Su, C.H.; Stassen, C.; Naha, R.; Ye, H.; Pepler, A.; Bell, S.S.; Dowdy, A.J.; Tucker, S.O.; Franklin, C. Performance and process-based evaluation of the BARPA-R Australasian regional climate model version 1. *Geosci. Model Dev. Discuss.* **2023**, *2023*, 1–34. [CrossRef]
33. Dupuy, J.-L.; Fargeon, H.; Martin-StPaul, N.; Pimont, F.; Ruffault, J.; Guijarro, M.; Hernando, C.; Madrigal, J.; Fernandes, P. Climate change impact on future wildfire danger and activity in southern Europe: A review. *Ann. For. Sci.* **2020**, *77*, 35. [CrossRef]
34. Boé, J.; Somot, S.; Corre, L.; Nabat, P. Large discrepancies in summer climate change over Europe as projected by global and regional climate models: Causes and consequences. *Clim. Dyn.* **2020**, *54*, 2981–3002. [CrossRef]
35. Naumann, G.; Cammalleri, C.; Mentaschi, L.; Feyen, L. Increased economic drought impacts in Europe with anthropogenic warming. *Nat. Clim. Chang.* **2021**, *11*, 485–491. [CrossRef]
36. Overpeck, J.T.; Udall, B. Climate change and the aridification of North America. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 11856–11858. [CrossRef]
37. Maxwell, J.T.; Bregy, J.C.; Robeson, S.M.; Knapp, P.A.; Soulé, P.T.; Trouet, V. Recent increases in tropical cyclone precipitation extremes over the US east coast. *Proc. Natl. Acad. Sci. USA* **2021**, *118*, e2105636118. [CrossRef]
38. White, E.E.; Ury, E.A.; Bernhardt, E.S.; Yang, X. Climate Change Driving Widespread Loss of Coastal Forested Wetlands Throughout the North American Coastal Plain. *Ecosystems* **2021**, *25*, 812–827. [CrossRef]
39. Pascale, S.; Carvalho, L.M.V.; Adams, D.K.; Castro, C.L.; Cavalcanti, I.F.A. Current and Future Variations of the Monsoons of the Americas in a Warming Climate. *Curr. Clim. Chang. Rep.* **2019**, *5*, 125–144. [CrossRef]
40. Liu, J.; Hagan, D.F.T.; Liu, Y. Global Land Surface Temperature Change (2003–2017) and Its Relationship with Climate Drivers: AIRS, MODIS, and ERA5-Land Based Analysis. *Remote Sens.* **2020**, *13*, 44. [CrossRef]
41. Beillouin, D.; Cardinael, R.; Berre, D.; Boyer, A.; Corbeels, M.; Fallot, A.; Feder, F.; Demenois, J. A global overview of studies about land management, land-use change, and climate change effects on soil organic carbon. *Glob. Chang. Biol.* **2021**, *28*, 1690–1702. [CrossRef]