Deploying Artificial Intelligence for Climate Change Adaptation

Walter Leal Filho[ab], Tony Wall[c], Serafino Afonso Rui Mucova[d], Gustavo J. Nagy[e], Abdul-Lateef Balogun[f], Johannes M. Luetz[g], Artie W. Ng[h], Marina Kovaleva[i*], Fardous Mohammad Safiul Azam[j], Fátima Alves[k], Zeus Guevara[lm], Newton R Matandirotya[no], Antonis Skouloudis[p], Asaf Tzachor[q], Krishna Malakar[r], Odhiambo Gandhi[s]

[a] School of Science and the Environment. Manchester Metropolitan University. All Saints Building. Oxford Road. Manchester M15 6BH. UK [b] Hamburg University of Applied Sciences, Research and Transfer Centre "Sustainable Development and Climate Change Management", Ulmenliet 20, D-21033 Hamburg, Germany. E-mail: walter.leal2@haw-hamburg.de

[c] Liverpool Business School, Liverpool John Moores University, Liverpool, L3 5UX, UK
Email: t.wall@chester.ac.uk ORCID:
0000-0003-2334-3279

[d] Faculty of Natural Sciences, Lúrio University, Pemba 958, Mozambique
Email: serafinomucova@ua.pt
ORCID: 0000-0001-7637-0671

[e] Instituto de Ciencias Ambientales y Ecología, Universidad de la República, Iguá 4225, 11200 Montevideo, Uruguay. E-mail: gnagy@fcien.edu.uy [f] Geospatial Analysis and Modelling Research Laboratory, Department of Civil & Environmental engineering, Universiti Teknologi PETRONAS (UTP), Persiaran UTP,
32610 Seri Iskandar, Perak, Malaysia Email:
alateef.babatunde@utp.edu.my

[g] School of Law and Society, University of the Sunshine Coast, Maroochydore QLD 4558, Australia; School of Social Sciences, University of New South Wales (UNSW), Sydney NSW 2052, Australia
Email: j.luetz@unsw.edu.au
ORCID: 0000-0002-9017-4471

[h] Waterloo Institute for Sustainable Energy, University of Waterloo, 200 University Avenue West Waterloo, Ontario, Canada; Global Centre for ESG Education and Research, The Hong Kong Management Association, Hong Kong SAR.
Email: awng@uwaterloo.ca ORCID: 0000-0002-1388-5835 [i] Hamburg University of Applied Sciences, Research and Transfer Centre "Sustainable Development and Climate Change Management", Ulmenliet 20, D21033 Hamburg, Germany.
Email: Marina.Kovaleva@haw-hamburg.de
[*] Corresponding author

[j] School of Life Science**,** Neijiang Normal University, Dongtong Road, Dongxing District, Neijiang, Sichuan, China
Email: shojibbiotech@yahoo.com

ORCID: 0000-0002-9337-273X
[k] Universidade Aberta & Centre for Functional Ecology, University of Coimbra, Portugal, Palácio Ceia, Rua da Escola Politécnica, n.º 147 1269-001 Lisboa – Portugal
Email: fatimaa@uab.pt ORCID: 0000-0003-2600-8652
[l] School of Government and Public Transformation, Technologico de Monterrey, Mexico City, Mexico [m] Escuela de Gobierno y Transformación Pública, Av. Revolución 756, Piso 2, 03700, Benito Juárez, Mexico City, Mexico.
Email: zeus.guevara@tec.mx ORCID 0000-0002-1254-8423
[n] Unit for Environmental Sciences and Management, North-West University, Private Bag X6001, Potchefstroom, 2520 South Africa
[o] Kgotso Development Trust, P.O. Box 5, Beitbridge, Zimbabwe
Email: runyamore@gmail.com
ORCID: 0000-0003-3836-497X [p] Department of Environment, University of the Aegean, University Hill, GR 81132,
Mytilene – Lesvos, Greece Email: skouloudis@aegean.gr
[q] Centre for the Study of Existential Risk (CSER), University of Cambridge, 16 Mill Lane, Cambridge, CB2 1SB, United Kingdom
Email: asaf.tz@gmail.com ORCID: 0000-0002-4032-4996 [r] Department of Humanities and Social Sciences, Indian Institute of Technology Madras, Chennai, Tamil Nadu 600036, India.
Email: krishnamalakar26@gmail.com
ORCID: 0000-0002-4225-4696
[s] Institute for Climate Change & Adaptation (ICCA), University of Nairobi, P.O. Box 30197-00100, Nairobi, Kenya
Email: hnrgandhi@gmail.com
ORCID: 0000-0003-0985-8495

Deploying Artificial Intelligence for Climate Change Adaptation Abstract

Artificial Intelligence (AI) is believed to be of potential use in tackling climate change. This paper explores the connections between AI and climate change research as a whole and its usefulness in climate change adaptation efforts in particular. Using a

systematic review of the literature on applications of AI for climate change adaptation and a questionnaire survey of a multinational and interdisciplinary team of climate change researchers, this paper shows the various means via which AI can support research on climate change in diverse regions, and contribute to efforts for climate change adaptation. The surveyed articles are classified under nine areas, e.g., Global/Earth Related; Disaster Response; Water-related Issues and Agriculture, 95% of which are related to adaptation. The areas that have attracted the most studies about AI application are water-related management issues (38%). In terms of the survey results, the most robust agreements were noted concerning the capacity of digitisation and AI to strengthen governance practices and policy coherence in climate change. Evidences gathered in the study suggest that, provided that due care is taken, the use of AI can provide a welcome support to global efforts to better understand and handle the many challenges associated with a changing climate.

Keywords: Artificial Intelligence, digital technologies, climate change adaptation.

1. Introduction: Using Artificial Intelligence in Climate Change Research

The notion of Artificial Intelligence (AI) indicates the abilities of machines to "learn from experience, adjust to new inputs, and perform human-like tasks" (Duan et al., 2019, p. 63) to "interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein, 2019, p. 17). Recent developments in AI have triggered significant breakthroughs and consequences across all aspects of human life. At the same time, the value of AI is estimated to reach up to $16 trillion by 2030 (Walsh et al., 2020). Even though an overarching definition for AI remains an elusive task, it is commonly accepted that such disruptive technological advancements open up new possibilities in the automation of repetitive and, usually, time-consuming tasks, offer new opportunities to pattern recognition in large amounts of unstructured data and integrate the self-learning of novel algorithms (Bhatia, 2017; Ghallab, 2016). Representing a new era in the knowledge society, AI brings new opportunities to interpret external datasets, imitating human cognitive functions and addressing complexities linked to human thought or feelings (Kaplan and Haenlein, 2019; Russell and Norvig, 2016; Martınez-Miranda and Aldea, 2005).

AI has penetrated most aspects of our life and its massive power, coupled with big data, is evolving geometrically. AI is bound to alter production processes across all business sectors and foster advanced, innovative and long-term solutions to pressing sustainability challenges. Under the scope of sustainability-oriented research. AI is employed through supervised, unsupervised or semi-supervised machine learning models, pertaining to algorithms that predict, identify and/or inherent patterns from labelled, unlabelled or semi-labelled input data, respectively (Nishant et al., 2020; García et al., 2019). Generalised linear models, decision trees, cognitive computing, support vector machines, Bayesian and artificial neural networks are some AI models gaining traction in the past few years (Shrestha and Mahmood, 2019; Şerban and Lytras, 2020). Natural computing is a subfield aimed at algorithm optimisation utilising biophysical material as computational media and simulating environmental phenomena in computers (Brabazon et al., 2015). Expert systems are also emerging themes linked with AI's capacity to solve complex problems of the natural world, such as climate change impact assessments, and aid decision-making by relying on specific knowledge and inference derived from databases and inference engines (Leo Kumar, 2019; Nishant et al., 2020).

Walsh et al. (2020) pinpoint key attributes describing the interactions between the global climate system and human psychology. Such attributes refer to our inability to comprehend the impacts of climate change due to their extreme scale and duration, our (mere) reliance on predictive models that encapsulate risks and uncertainty, the remoteness of climate change impacts in terms of space as well as time, and the inherent common-pool resource constraints of anthropogenic GHG emissions that hamper collective mitigation actions. These properties explain why climate change affects livelihoods and incurs multidimensional impacts, spanning from rising temperatures and increased frequency in extreme weather events to the aggravation of socioeconomic inequalities and human diseases. In this context, the computational architecture and power that AI encapsulates are particularly fitting in grappling with such pressing climate change threats, a domain of global environmental changes described by massive data availability, processing and forecasting challenges (Stein, 2020). Multi-sensor-driven AI tools and blockchain platforms can optimise circular economy loops (Kouhizadeh and Sarkis, 2018; Kouhizadeh et al., 2019; Adebiyi-Abiola et al., 2019; Wang and Qu, 2019), giving room to sustainability transitions that reduce the carbon footprint and uncontrolled disposal of solid waste (Sankaran, 2019) as well as our dependence on primary (non-renewable) resources. Likewise, neural or sensor networks, machine learning, and cognitive computing can bring profound energy management and optimisation capabilities and smart urban planning and design (Şerban and Lytras, 2020). Utilising such AI advances can yield unprecedented advantages in analysing interconnected, large-scale databases to minimise the carbon intensity of systems, model possible climate change impacts and maximise resource efficiency through smart grids and connected smart appliances. Neural networks and smart algorithms, in particular, can also contribute to developing joint actions aimed at preserving the ecosystem's health and biological diversity, combat desertification, soil degradation and marine pollution (e.g. Keramitsoglou et al., 2006; Mohamadi et al., 2016; Kwok, 2019; Nunes et al., 2020; Vinuesa et al., 2020). It is well-established in the literature that emphasising carbon neutrality in electricity production and distribution, transportation, agriculture, as well as construction and buildings can have tremendous benefits in climate change mitigation and, in this respect, AI can be a critical agent of change (e.g. see Stein, 2020). AI applications may also upscale climate engagement of the public and stimulate collective action by predicting or visualising climate change risks and aid decision-support efforts by monitoring extreme weather disasters (remotely and) in real-time (Alemany et al., 2019; Huntingford et al., 2019; Walsh et al., 2020).

For example, AIDR (Artificial Intelligence for Digital Response) assists relief organizations by analyzing big data, that is, tweets, to detect the location and impacts of floods (Imran et al., 2014). There are other AI models that can immensely help disaster relief by mapping floods, locating refugee camps using satellite data (Logar et al., 2020) and determining the populations requiring the most help (Omdena & WFP, 2020). Indeed, AI advancements in climate big data processing allow for the identification of much more comprehensive future climate change scenarios and intelligent early warning systems. Projects like EnviroAtlas offer actionable insights into climate change implications on societies, ecosystems and healthcare (Manogaran and Lopez, 2018). For instance, ambient intelligence using sensor networks provides real-time climate data (Dingli et al., 2012; Ribeiro and José, 2013) and brings new opportunities in monitoring climate change impacts and disease forecasting and surveillance (Booth, 2018; Waits et al., 2018; Manogaran and Lopez, 2018). AI is also useful for assessing impacts of climate change on agriculture. Crane-Droesch, A. (2018) has developed a machine learning based model that can predict corn production under different climate change scenarios. Jakariya et al. (2020) has developed a mobile application using machine learning methods that can assess vulnerability of farmers in coastal Bangladesh based on an individual's responses to a questionnaire.

Nevertheless, AI applications aiming to endorse environmental sustainability are challenged by the rebound effects of high energy-intensive structures, undermining efforts to achieve carbon-neutrality and avoiding overexploitation of primary resources. For example, server operating systems that execute essential AI computational tasks (or store big data) entail considerable energy for cooling and unhindered operation. At the same time, their production, service and final disposal require vast amounts of nonrenewable materials (such as lithium, nickel or cobalt) and efficient e-waste management, respectively (Kaplan and Haenlein, 2020). By performing a comprehensive review of the available literature, Nishant et al. (2020) also point out as significant challenges posed by AI-based applications the overreliance on historical data in machine learning models, undesirable human responses to AI interventions, the underlying cybersecurity risks and possible adverse impacts of AI applications as well as a lack of holistic metrics for AI performance measurement.

Moreover, before launching AI deployments, it is crucial to increase the awareness of risks associated with likely failures of AI systems in a society progressively more dependent on this technology (Vinuesa et al., 2020). Related challenges in climate big data in the global earth observation system are outlined in Faghmous and Kumar (2014), Lee and Kang (2015) and Nativi et al. (2015). Crucially, underlying gaps in ethical, transparency, equality and safety standards stemming from such challenges call for regulatory insights and appropriate legislation frameworks to address counterproductive outcomes from AI penetration patterns (Kaplan and Haenlein, 2020; Vinuesa et al., 2020; Petit, 2018).

Overall, digital technologies (DTs) are transforming societies and accelerating achievements faster than any previous innovation over last two decades (United Nations, 2020). Digitalization and digital economies additionally trigged by the COVID-19 pandemic (MIT Initiative on the Digital Economy, 2021) significantly contribute to climate actions (Balogun et al., 2020; Li et al., 2021; Dwivedi et al., 2022). DT itself can potentially directly reduce global emissions up to 15% by 2030 and additional 35% by impacting on transformation of systems as well as business and consumers decisions (Falk et al. 2020).

Given the above and taking into account that AI research and development can be a significant game-changer towards advanced, innovative and long-term solutions to pressing climate change threats, this study aims to review AI applications for climate change adaptation. We used a systematic review of the literature on these subjects based on an online survey to achieve this. The paper is structured as follows. The next section describes the relation between AI and Climate Change Adaptation. Further, section 3 presents the methods used, namely an expert-driven systematic literature review complemented by a global online survey. Section 4 discusses the main results. Section 5, the conclusions section, summarises implications of the paper and outlines future prospects. The paper ends with two Appendixes. Appendix 1 (Systematic Literature Review with a data matrix which summarises examples of the articles used and their references) and Appendix 2 which includes the survey instrument deployed in the study.

2. Artificial Intelligence and Climate Change Adaptation

AI and its subset of machine learning have drawn significant attention in recent years. The influence of such technology on human life has increased due to the improved connectivity, data storage and processor speed. AI is frequently used in many sectors such as health and transport (Huntingford et al., 2019); renewable energies (He et al., 2021); education (Shaikh et al., 2021); construction industry (Abioye et al., 2021); ocean dynamics (Zhao and Du, 2021); environmental quality control (Liu et al., 2021); biodiversity (Li, 2020); agriculture (Liu et al., 2021). Yet, for climate change adaptation, AI is used in the cities and mobility sustainability (Balogun et al., 2020); housing cooling system (Ahmed et al., 2021); water sustainability (Doorn, 2021); energy sustainability (Ahmad et al., 2021).

Although AI and machine learning are helpful in climate change adaptation, their combined use was previously neglected due to the lack of power and computer capacities, which is particularly important as climate change is a data-intensive issue with various subsets. However, recent advancements enable scientists to incorporate AI into climate change adaptation (Huntingford et al., 2019).

AI may be used in multiple ways to increase adaptation to climate change, to the same extent that climate-smart technologies do (Tran et al., 2020). Firstly, systems may be designed to monitor meteorological measurements using high resolution and spatial data. Secondly, machine learning can be used to draw links between location, time, and changes of the meteorological measurements. After that, interpreted data can be fed into artificial intelligence systems that provide automated warnings to people about erratic weather patterns and extreme weather events caused by climate change (Huntingford et al., 2019).

Scientists are now able to combine machine learning with climate models. Machine learning is valuable, as it helps to solve previous problems by offering accurate results that are less expensive than older models. Previous models faced difficulties dealing with large amounts of data. However, machine learning can efficiently process data faster, which is beneficial in predicting extreme weather events, and models are now being redesigned or modified to include machine learning (Rolnick et al., 2019).

Climate change has a significant societal impact that translates to ecological and socioeconomic issues in a given country. Machine learning has uses in alerting citizens by identifying and prioritising areas of high risk. Besides, it may provide annotation by using raw data and promoting exchange, making it easier for data to be shared, allowing people to develop adaptation methods by deciding on the highest risks and using shared information to generate solutions (Rolnick et al., 2019).

With regards to ecology, AI is used to monitor live ecosystems and track biodiversity. By tracking species and their numbers, conservationists can decide areas of high priority and low priority. Furthermore, machine learning is used in the form of imagebased sensors to monitor biodiversity. These are automatically triggered by movement, and cameras capture pictures that can be used to classify species (Rolnick et al., 2019).

AI has great potential in the energy industry. The reduction of fossil fuels used requires that the energy crisis be addressed, which, in turn, will reduce the climate change impacts and make adaptation easier (Walsh et al., 2020). A key example is Google using machine learning to increase wind generation efficiency and predict power output, increasing the value of their wind energy by a 20% factor (Elkin & Witherspoon, 2019). Promotion of alternative energy sources aids in lowering carbon emissions. In similar ways, AI and machine learning can be used to regulate building energy and thus can be applied to the construction of intelligent cities (Rolnick et al., 2019; Walsh et al., 2020)

3. Methods

This paper seeks to identify the nexus between AI and climate change adaptation in a sample of countries known to be investing resources on AI for various climate change adaptation purposes primarily based on a systematic literature search that was implemented, adapting the model used by Leal Filho et al. (2019). The following data collection and analysis steps were conducted sequentially: Identify data sources; select pieces of pertinent literature; perform critical evaluation of studies; distill synthesis of acquired prior studies and document essential findings. This systematic method facilitates the aggregation of a significant volume of information in the search, thereby offering detailed and reliable information for diverse stakeholders in the AIclimate change adaptation domain.

Care was taken to select reliable sources for the research data since top quality resources are essential requirements for a good literature search (Balogun et al., 2020). Literature searches were based on some of the most reputable online databases of scientific research data, including Web of Science, Scopus, and Google Scholar. We also consulted reports from specialised organisations (e.g. research centres and societies, UN bodies, and the OECD). In addition, the scope of literature sources was extended to include search engines (e.g., Google) to ensure that relevant publications which are not included in scientific databases were not omitted. The parameters analysed in such literature include (i) Theme/Category, (ii) AI Application, (iii) Implications, (iv) Region.

Further, to complement the above mentioned systematic literature review, a global online survey based on a questionnaire was administered, with a focus on DTs and AI for climate change adaptation.

The structured questionnaire survey was made available to respondents for approximately two weeks in February 2021 through the online Google forms platform tool. The survey design was deployed with a view to catering for a 'rapid turnaround in data collection' (Creswell and Creswell 2018, p. 149). It was supplemented by a critical expert literature analysis (Machi and McEvoy 2016), which provided a robust foundation for the execution of this research.

Overall, the survey instrument comprised sixteen closed-ended questions, of which three questions offered scope for a brief qualitative analysis. The survey questions were designed to probe aspects of research relevance at the intersection of AI and climate change management. The questions were organised into the categories of 'general questions' (e.g. What is your climate change research oriented towards?) and 'technical questions' (e.g. In which areas do you see a promising use of DTs and AI in climate change context?). The data collection instrument was developed through an iterative process that solicited input and feedback from a multinational and interdisciplinary team of climate change researchers. Following the instrument's conceptual development, the data collection instrument was pre-tested, which led to minor adjustments, but overall confirmed its adequacy (Bryman 2016, pp. 260-261).

The purposive sampling ensured that the survey instrument was appropriate for the envisaged target group, which comprised academics working in disciplines related to climate change, including mitigation and adaptation. Additionally, a snowball sampling was used to leverage the research networks of the authors and 'capitalise on the connectedness of individuals in research networks' (Bryman 2016, p. 415). The participation in the survey was solicited by email during the above stated data collection time frame.

The subsequent descriptive statistical analysis allowed the researchers to characterise the prominent trends (Punch 2014, Creswell 2013, 2014). Selected respondent comments, to which our analysis refers in some places of this paper, resulted from those three questions which allowed respondents to provide qualitative answers. The qualitative responses were analysed through a content analysis using coding and categorisation (Creswell and Creswell, 2018). The inferential analysis of the data was performed using the statistical software SPSS. Statistical significances for variables were determined using Pearson's chi-square test (if Chi-square < 0.05 = Significant; if > 0.05 = Non-significant) (Bryman 2016, p. 347).

4. Results and Discussion

Systematic literature review

The systematic literature review has assessed the current research areas in applying AI and climate change. Appendix 1 provides a summary of the identified research publications, which are categorised under the Adaptation or Mitigation category. Each article is further classified under the following main areas: 1 = Global or Earth Related; 2 = City or Urban Related; 3 = Disaster Response; 4 = Water-related Issues; 5 = Agricultural, Land or Tree; 6 = Energy; 7 = Wildfire; 8 = Specific AI Technique (s). Around 95% of these studies are related to climate change adaptation, whereas 5% of them refer to mitigation. In particular, the use of AI for adaptation is frequently performed for monitoring climate dynamics, and in predicting the adverse impacts of climate change in cities and the urban environment. Making other areas, AI is deployed to develop sophisticated modelling and forecasting for evaluating vulnerabilities of different regions of the world. This approach is considered relevant to policy and decision-makers in environment planning and action plan formulation, in light of potential disasters and adversities to human health. From a risk management perspective, the use of AI in this context is useful in anticipating scenarios that could be dealt with, by formulating measures to reduce possible climate change impacts, and even avoid potential losses due to climate-associated problems where conceivable.

The assessed studies were either reviews (4), case studies (17), or experimental studies (35). The case studies involved Asia (8), Europe (6), Australia (2), and North America (1), respectively. Nearly half of the literature assessed (27 out 56) focused heavily on the significant role of AI in understanding future outlooks, where issues related to forecasting, projection, and modelling of extreme weather events, resource use, and the even impact of conservation and adaptation efforts were predominant.

In terms of humanitarian responses in the wake of extreme weather events, fewer than ten studies addressed the application of AI in disaster risk reduction and response.

Similarly, little attention was given to AI's role in unlocking the blue economy's potential, as only six studies underscored its application in inland and natural coastal capitals. Among the literature assessed, AI was noted to have gained traction in terms of its application in biotechnology, agronomy, and plant science, particularly at a time when drought and pest-resistant crop varieties are most sought in many places around the world. The place of AI in the clinical characterisation of mental health cases emerged only once where virtual reality (VR) is relevant in assessing, treating, and managing posttraumatic stress disorder (PTSD). These findings echo the broad application areas previously studied, but extend previous studies by representing the spread and reach of AI application in climate change adaptation (Walsh et al, 2020)

Figure 1 reveals that 38% of studies pertinent to water-related issues under climate change, including flood prediction and irrigation management, have attracted the most research attention on examining the application of AI for adaptation.

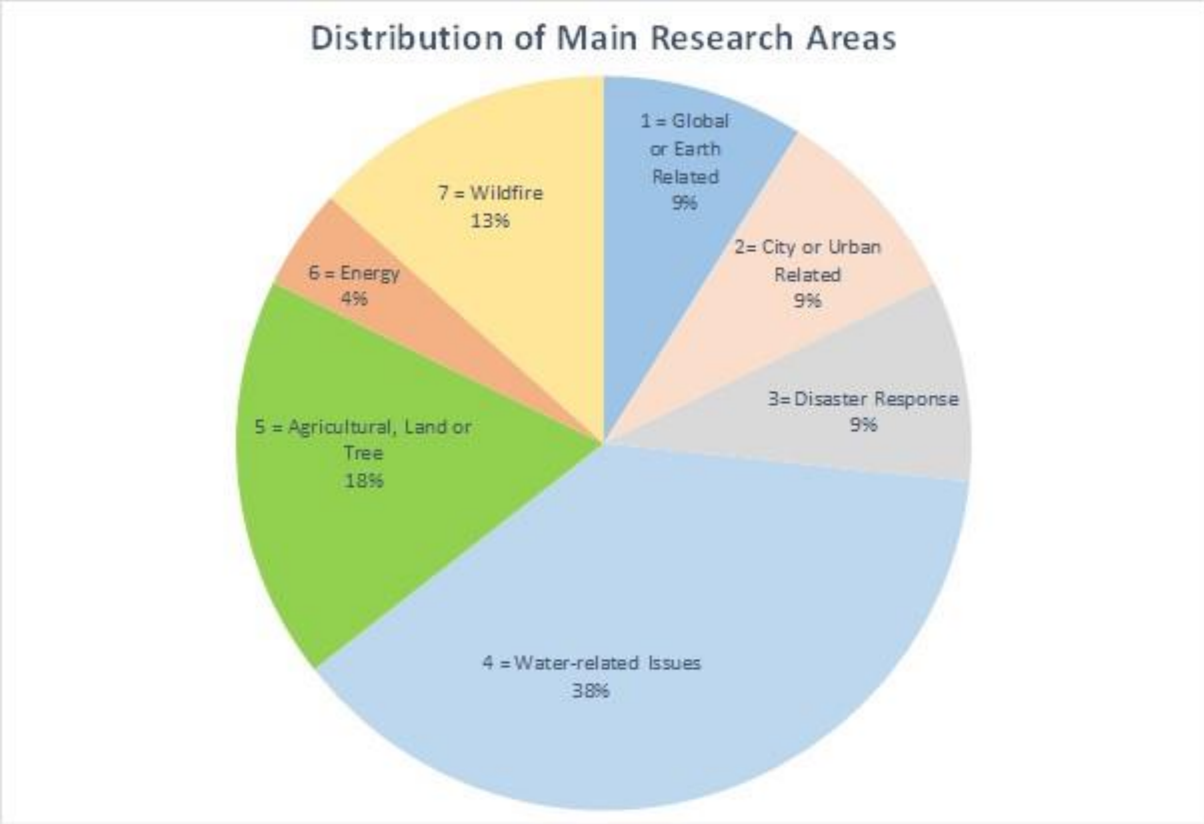


Figure 1. Distribution of main research areas on AI application by the identified research publications

These studies have examined the vulnerability of various regions to potential floods linked to climate change, and evaluated measures to adapt based on AI applications. The combined categories of agriculture, land and wildfire represent 31% of the sampled literature. These studies broadly reveal how AI is deployed to predict pertinent events that create challenges and risks to the inhabitants; possible solutions are derived. About 27% of the articles provide some reviews and assessments on the use of AI technologies to support climate change adaptation in disaster management, regional and global deployment potentials in general. The remaining 5% suggest the possible innovative deployment of AI for energy management, particularly to enhance renewable energy that mitigates greenhouse gas emissions and climate change. Contrary to previous studies, this highlights the relative concentrated application of AI in relation to disaster management (Stein, 2020).

Survey

The systematic literature review was complemented by a survey of 104 respondents from 51 countries. The respondents came from all continents (Figure 2), with a majority coming from Africa at 32%, followed by Europe (31%). The lowest percentage contribution came from the Oceanic-Australia block, which contributed 3%.
Furthermore, the respondents varied among countries and the rate was 68% male and 30% female, whereas about 2% did not state their gender.

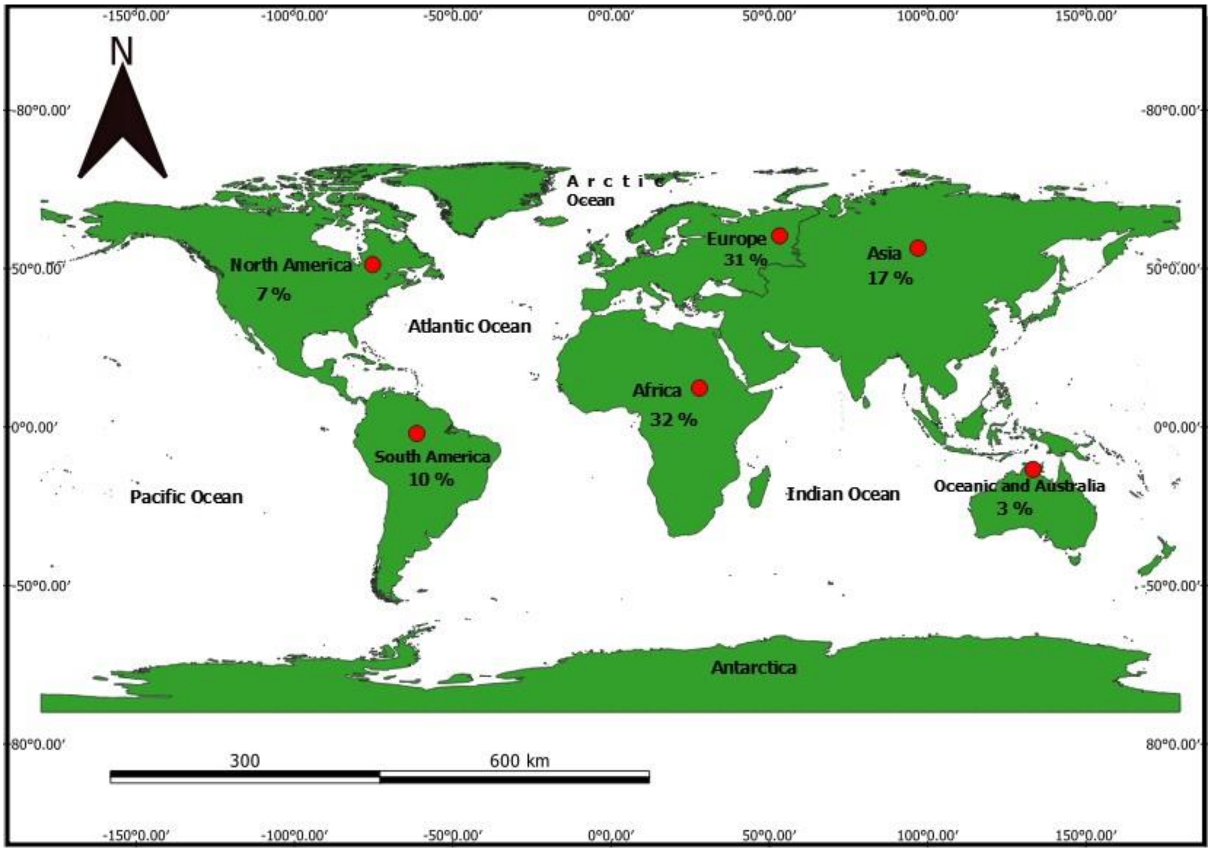


Figure 2. Spatial distribution of respondents

It was positive that Africa had the most survey participants. It is one of the continents is disproportionately affected by climate change; therefore, as part of building the adaptation capacity on the continent, participation in such studies is vital. Moreover, results from the systematic review indicated that comparatively few case studies from the continent are document. Thus, number of African respondents to the survey can offer valuable insights to make up for the absence of case studies from the region.

Even though South America, Australia and Oceania did not have a high number of participants, these continents are also expected to suffer several adverse climate change effects; hence adaptation capacity may be increased by integrating AI and other related DTs.

Respondents provided various types of replies to the questions posed (Table 1). The most robust agreements were noted concerning the capacity of digitisation and AI to 'strengthen governance practices and policy coherence in climate change' (90%), to 'strengthen environmental sustainability and reduce climate vulnerability' (89%), and to 'deliver economic and environmental benefits in climate change management' (88%). These reflect the positive intentions of AI reported in the literature (Stein, 2020).

Table 1. Percentage responses on survey questions

Variable	Percentage response					Mean	Standard deviation
	Strongly Disagree d	*Disagree*	*Neither agree nor disagree*	*Agree*	*Strongly agree*		
Digital technologies and AI can strengthen governance practices and policy coherence in climate change	7	1	2	36	54	4.29	1.07
The implementation of timely and adequately designed digitallybased technologies and AI can deliver economic and environmental benefits in climate change management.	6	1	5	35	53	4.28	1.05
Digital technologies and AI can strengthen environmental sustainability and reduce climate vulnerability.	5	2	4	49	40	4.17	0.97
I fear the possible risks that digital technologies and AI can bring to mankind (e.g. algorithms, robots making decisions).	12	26	20	30	12	3.04	1.23
I fear the possible risks that digital technologies and AI can bring to employment (e.g. human redundancy).	9	24	22	32	13	3.16	1.20
Digital technologies and AI may help to mitigate the inequalities that are being exacerbated by climate change.	3	11	27	38	21	3.63	1.03
Limitations in digital connectivity disproportionately affect developing countries.	5	3	7	37	48	4.2	1.04
Leveraging digital technologies and AI may facilitate teaching and research on matters related to climate change.	6	1	9	44	40	4.11	1.03
Leveraging digital technologies and AI may accelerate progress towards the implementation of SDG13 (climate action)	6	3	10	40	41	4.07	1.08

There is a need to improve the sustainability dimension of teleworking, remote learning and virtual living to foster education on matters related to climate change	6	1	11	37	45	4.14	1.06
There is a need to keep the public well informed, with full transparency and accountability	5	3	2	31	59	4.36	1.03
Digitalisation and AI will be deployed much faster and on a wider scale than in the past	6	1	11	35	47	4.16	1.07
The use of digitalisation and AI needs to be paralleled by privacy and data protection procedures	7	2	2	29	60	4.33	1.11
Enhancing the use of digital technologies and AI will be critical for a climate-resilient and sustainable COVID-19 pandemic recovery	5	4	12	33	46	4.11	1.09

However, there was also a recognition of the 'need to keep the public well informed, with full transparency and accountability' (90% of respondents agreed or strongly agreed), 'the use of digitalisation and AI needs to be paralleled by privacy and data protection procedures' (89%), and that the 'limitations in digital connectivity disproportionately affect developing countries' (85%), which demonstrates a balanced view of both the benefits and implications of digitisation and AI in climate change research and practice. Whereas the former of these reflect the extant literature, the latter points to broader awareness of the inequalities that has hitherto not been so explicit (Walsh et al, 2020).

Responses on the relevance of DTs and AI to climate change action were mixed across the continents (Figure 3a). Respondents from Australia demonstrated the most affirmative responses (where 100% of respondents replied 'very important and frequently used' or 'important and sometimes used'). North America and South America offered the subsequent highest affirmative responses (80% and 75%, respectively).

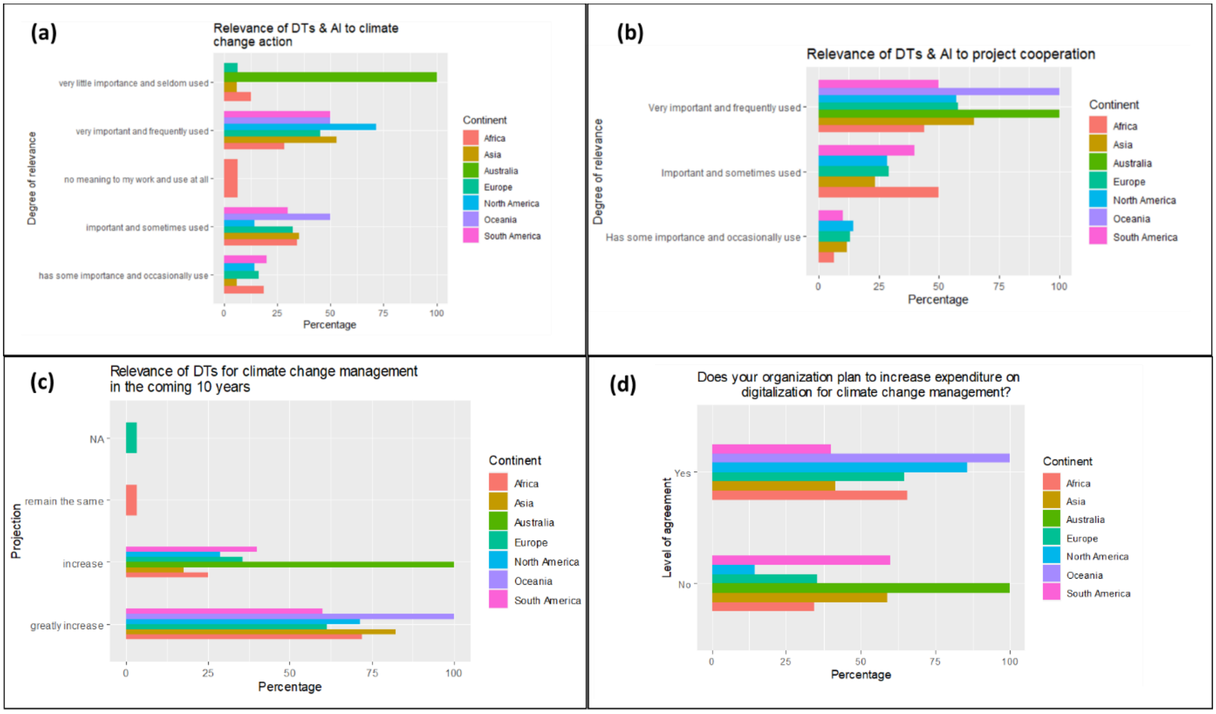


Figure 3. Relevance of digital tools and AI to (a) climate action (b) project cooperation (c) climate change management in the next ten years (d) organisational expenditure on digitalisation for climate change

The only continent with respondents reporting ‘no meaning to my work and uses at all’ was Africa (5%). These findings might reflect limited national resources and the stage of technology diffusion in climate change action across the continents. For instance, many farmers in Africa still rely on rainfed agriculture, increasing vulnerability to impacts of climate change (Serdeczny et al., 2017). Moreover, digital data on local climate projections and weather forecasts to support optimal farming practices in the region is scarce (Balogun et al., 2020), aligning with the findings of this study. However, such findings are consistent with the aforementioned finding related to the unequal access to resources such as AI and DTs which is hitherto largely absent in the extant literature (Walsh et al, 2020).

Similarly, the adoption of DT for climate change adaptation in North America has been documented in earlier studies. An example is the United States' Southeast Climate Consortium's (SECC) agrometeorological program aiding the management of climate risks in the past decade. With this initiative, digital tools are used to simplify and communicate complex climatic concepts to enhance farmers' understanding and awareness of climate impacts on agriculture (AgroClimate, 2015). In contrast to previous studies, this finding highlights the differential application of AI and DTs across countries in relation to climate change adaptation (Alemany et al, 2019).

The relevance of DTs and AI to project cooperation was affirmative across all continents (Figure 3b). As noted, the most affirmative responses were in Oceania and Australia, with 100% of respondents reporting 'very important and frequently used'. The answer 'has some importance and occasionally used' was most commonly reported in North America (13%), Europe (12%), and Asia (10%). These findings reflect the widespread use of communications technologies in project activity across all continents, and is an aspect not typically reported in previous studies about the use of AIs and DTs in climate change adaptation (e.g. Stein, 2020). In its study of the application of digitalisation for sustainable development in the global north and south, Balogun et al. (2020) reported the prevalence of DTs (e.g., big data analytics) in all continents to enhance urban resilience. Also, Mckinley et al. (2021) highlighted the emergence of innovative digital tools, methods, and approaches to support a wide range of project cooperation, including aspects of climate change action. The extended employment of DTs is evident during the COVID-19 pandemic to facilitate stakeholder engagement, project cooperation, communication, research and teaching (Leal Filho et al., 2021a). Notably, the relevance of DTs and AI for future climate change management (Figure 3c) is overwhelmingly expected to 'increase' or 'greatly increase' by respondents in all regions.

In terms of predicted future institutional investments in digitisation (Figure 3d), findings indicated affirmative results from Oceania (100%), North America (85%), Africa (64%), and Europe (63%). In contrast, respondents from the following indicated no further investments: Australia (100%), South America (58%) and Asia (57%). These results might reflect current commitments to maintain technological advancements in ongoing climate change activity (e.g. in Oceania) or potential maintenance and utilisation of previous institutional investments in technology (e.g. as demonstrated in China and other parts of Asia in recent years). These findings add new insight into the perception of ongoing investment in AI, an area currently unexplored in the literature (Walsh et al, 2020), but indicative of future intent and activity.

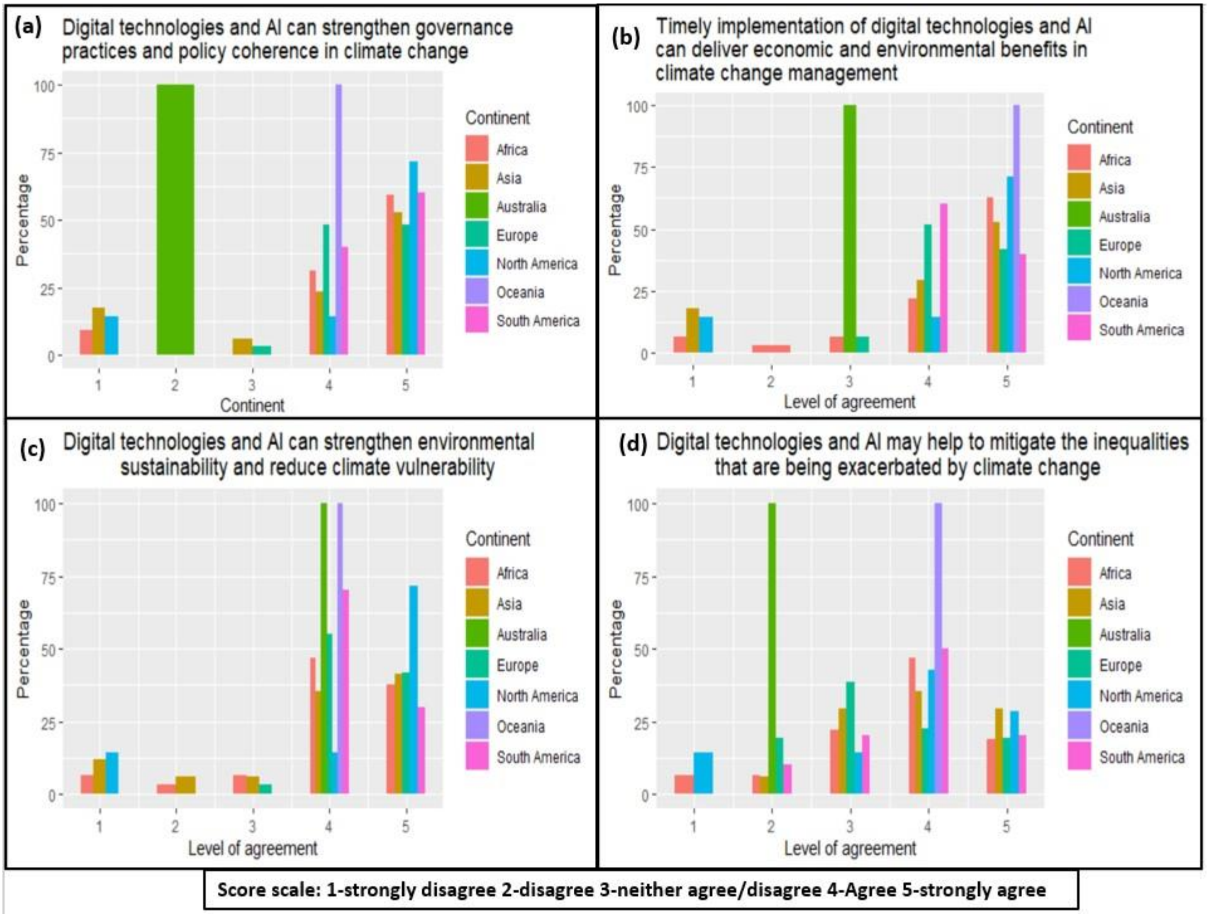
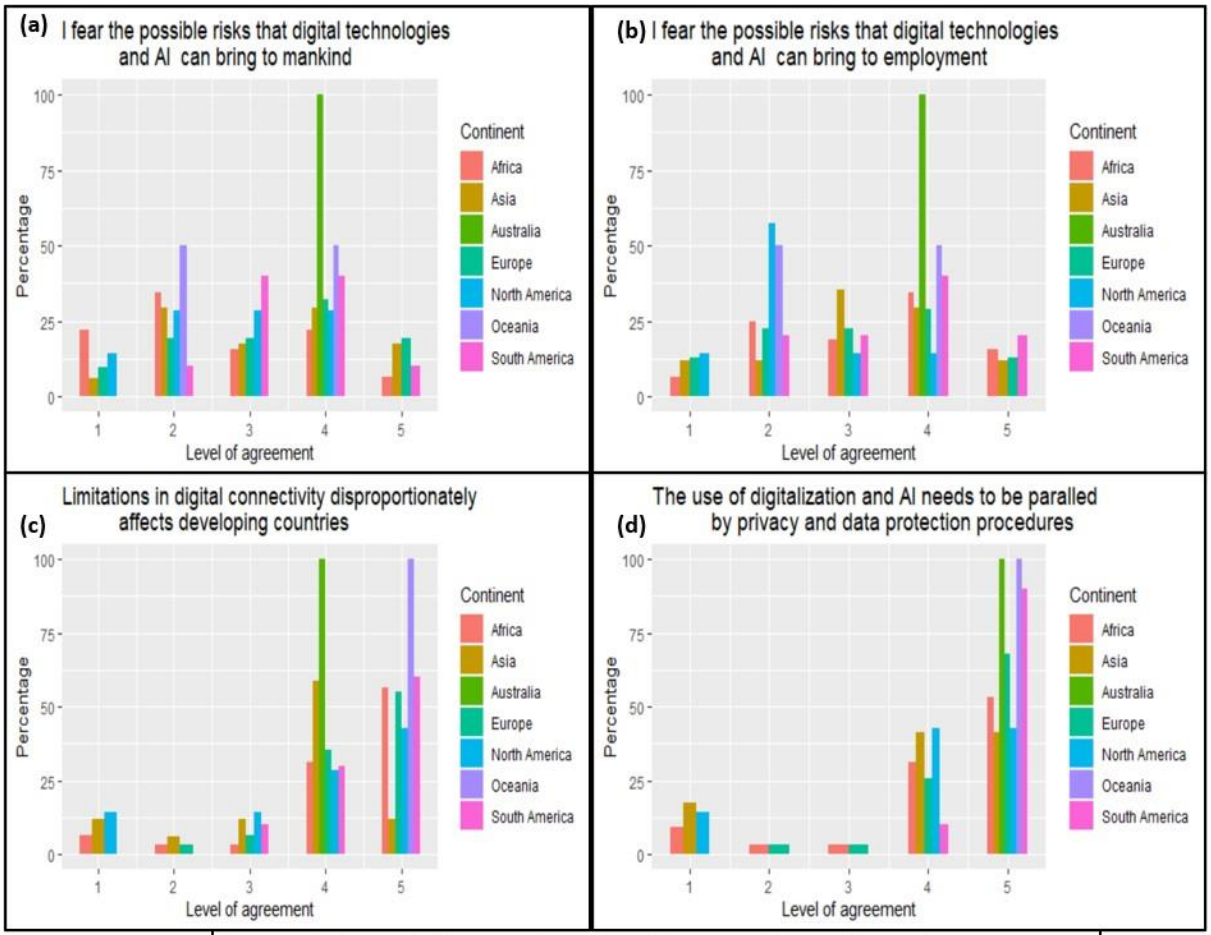


Figure 4. The capacity of DTs and AI to (a) strengthen governance and policy coherence, (b) deliver economic and environmental benefits, (c) strengthen environmental sustainability and reduce climate vulnerability, and (d) mitigate the inequalities from climate change.

The survey indicated that 54% of respondents disagreed that DTs will strengthen the governance practice and policy coherence in climate change (Figure 4a). In comparison, 36% agreed that DTs could be of assistance in the development of climate change governance policies, which can be linked to the detachments that often exist between policymakers and advancements in scientific fields. Furthermore, the governance sphere is a complicated field that is often a contested terrain among policymakers and politicians alike. Therefore, it is imperative that even though DTs can be proven tools in improving governance, vested interest also needs to be taken into account during policy formulation. From a continental angle, respondents from Oceania and Australia totally agreed with the view; however, this analysis needs to be treated with caution due to the small size of the sample from the two continents. These findings sit in contrast to previous findings as they provide a more skeptical picture of how AI can be applied in policy and governance fields (Rolnick et al, 2019).

Concerning that the timely implementation of DTs and AI deliver economic and environmental benefits in climate change management (Figure 4b), most respondents agree (particularly from South America and Europe) or strongly agree (particularly from Oceania and Europe). Only the responses from Australia are neutral.

Regarding the capacity of DTs to reduce climate change vulnerability, 40% and 45% of respondents strongly agreed and agreed, respectively, that DTs might reduce climate change vulnerability, with the highest percentage coming from North America, besides the 100% from Australia and Oceania (Figure 4c). This aligns with the outcome of the literature review and confirms opportunities to use AI and digital tools to find practical adaptive approaches to climate change. Such tools include machine learning applications in climate change. This position was established by O'Gorman and Dweyer (2018). They asserted that machine learning helps reduce uncertainties associated with climate models, thus further affirming that AI can be a valuable tool in climate change. The exact position is also articulated and highlighted by Vinuesa et al. (2020), who assert that AI can be integrated with improving renewable energy capabilities and energy efficiency, thus reducing the total greenhouse gas emissions and carbon footprint. Finally, concerning DTs being a tool to reduce inequalities (Figure 4d), 38% of respondents agreed that digital tools could reduce inequalities due to climate change. Thus, most respondents in all regions (except Australia) expect DT and AI to strengthen governance practices and policy coherence in climate change.



Score scale: 1-strongly disagree 2-disagree 3-neither agree/disagree 4-Agree 5-strongly agree

Figure 5. Percentage response on risks posed by AI on (a) mankind (b) employment (c) limitations of developing countries (d) personal privacy

The survey respondents still hold considerable fear regarding the threat posed by DTs and AI to humankind, as confirmed by 30% of respondents indicating that AI and related technologies pose some danger (Figure 5a). The highest percentage of concern came from Australia (100%), Oceania (50%), and South America (38%). In comparison, respondents' in Africa only reflected a minor level of anxiety at 22%. Fears related to impacts on employment (Figure 5b) are nuanced and noticeable across all continents, although at close to 60% Europeans are more cautious than North Americans. Generally, apprehension stems from the belief that AI may create a superhuman with capabilities beyond human beings (Yu et al., 2018), eventually overtaking human beings and lacking consciousness (Dehaene et al., 2017). Respondents also strongly felt that connectivity and infrastructure issues could negatively affect the capacity of developing countries to take full advantage of advancements in AI and other digital tools (Figure 5c).

The fear of AI is further confirmed by respondents agreeing across all continents that there is a need for privacy and data protection procedures when applying AI (Figure 5d). Figure 5d shows agreement and convergence regarding digitalisation, and AI needs to be paralleled by privacy and data protection procedures for all regions. The Australia region, and Oceania, both with 100%, are the most positive or affirmative, if compared to the South America and European region, with more than 80% and 60%, respectively. Although Asia and North America are both positive, they had relatively lower values (both over 35%) than Australia and Oceania. Although Africa is considered a relatively backward region in the use and exploitation of advanced technologies, especially digitisation and AI, it presented a relatively higher value (more than 50%) when compared to North America and the Asian region. Whilst some of these fears have been previously reported, the extent and reach of these fears has not previously been reported on a global level (Stein, 2020). This is an important dimension to consider in further implementation and exploitation of AI for climate change adaptation.

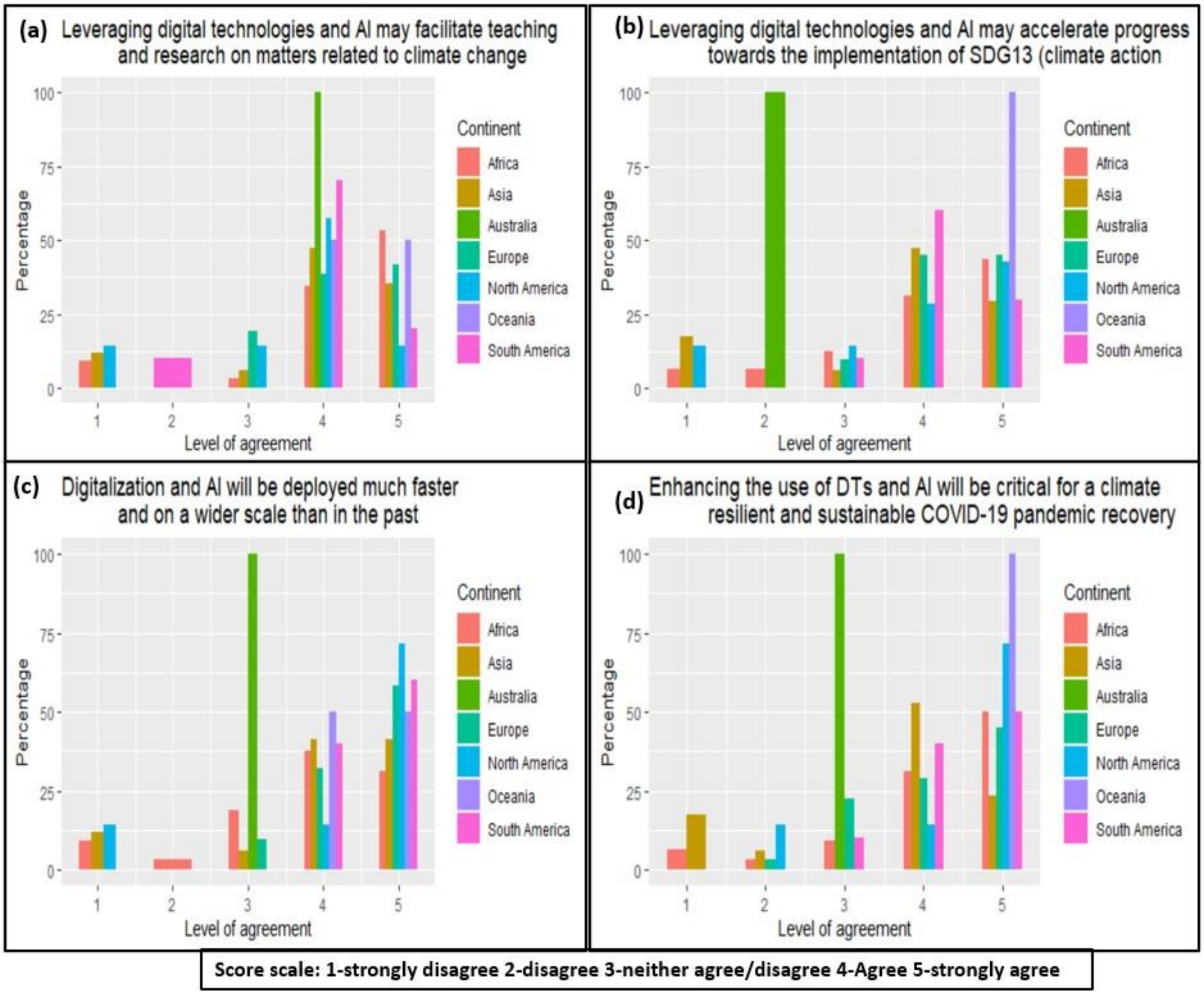


Figure 6. Leveraging digital tools and AI can assist in (a) teaching, and research (b) accelerating progress towards implementation of SDG13, (c) faster and broader scale deployment (d) enhancing climate resilience and post COVID-19 recovery

From the survey, 40% and 44% of respondents from across all the continents agreed that leveraging DTs and AI can be valuable tools in increasing research in climate change-related issues and the implementation of SDG13 (Figure 6a and 6b). On a continental level, 68% of respondents from South America felt that AI and related digital tools could assist as tools of research and assist in the implementation of SDG13. This view is supported by Belayneh et al. (2016), who assert that AI can easily be leveraged in drought forecasting, which can subsequently reduce the cost of food insecurity interventions as well as assist in saving lives. The use of AI in climate research and action is further advocated in Huntingford et al. (2019), who encouraged the use of models and data-driven machine learning to provide warnings and decision-making support, notably drought predictions. Similar opportunities for AI about disaster management and mitigation are noted by Sun et al. (2020) and Sayad et al. (2019), respectively. Our study findings are similar to Vinuesa et al. (2020), which established that AI could act as an enabler in achieving environmental-related outcomes, including SDG13.

On the other hand, 40% and 41% of respondents respectively, believed that AI and DTs would not be good tools to aid research in climate change and the implementation of SDG13 as some of the AI techniques are high energy demanders, and particularly where non-carbon neutral energy sources are used (Vinuesa et al., 2020).

The research results allow the authors to highlight the existence of imbalances on the understanding of technological advances, or whether digitalisation and AI will be deployed much faster and on a broader scale than in the past (Figure 6c). These disagreements, mainly in Africa, maybe associated in part due to limited use of technologies and digitisation in various productive sectors, limited information on the current dynamics of technologies and AI, and reduced opportunities for technological production and transformation (Van Rensburg et al., 2019; Cariolle, 2020). Furthermore, another set of risks can be classified as cyber physical and structural imbalances (Jelinek et al., 2021) thus limiting equitable AI adoption by all countries. However, the significant climate sensitivity, exposure, and reduced adaptive capacities in Africa consequently translate into major vulnerability (Ahmadalipour et al., 2019; Leal Filho et al., 2021b). This may require advanced technological options such as AI to detect, predict, record, and report extreme weather events, sudden events, predictability of impacts, and mitigation and adaptation options. Nevertheless, North and South America, with more than 80% and 75%, respectively, were more optimistic about the rapid advances in digitisation and accelerated implementation of AI. Such optimism could mean acquiring most of the knowledge, production capacity, technological transformation, and digitisation of these regions.

Consistent with responses to other questions, answers are skewed in favour of the expectation that the use of DTs and AI will be critical for a climate-resilient and sustainable COVID-19 pandemic recovery, with a clear majority of respondents in all regions (except Australia) expressing this expectation (Figure 6d). The Australian region, with 100%, is less favourable compared to all regions. A more positive affirmation was verified in the Oceania region, with 100%, and North America, with more than 65%. With more than 50%, Africa was more favourable than the Asian region (more than 40%) and Europe (more than 35%). We understand that the less favourable position of the Australian region (100%) can be justified likely due to (1) the existence of similar tools that can play and support climate resilience and sustainable COVID -19 pandemic recovery, and (2) climate change and COVID-19 pandemic are consequences of human behaviour, which can be positively changed, if there is a will, decision, commitment, and all this anchored to well-founded and effective policies.

The practical application of AI can be a valuable tool shown by Buckland et al. (2019). They established that ANNs could be applied in future predictions of future natural or human-induced disturbances of climatic systems. The practical application of AI is also further demonstrated in Mohamadi et al. (2016), where a trained AI system can track the desertification of regions. Furthermore, McGovern et al. (2017) indicated that AI could assist in improving forecast models as several AI techniques can extract information through blending observational data and forecast model information; hence quality outcomes can be derived. Furthermore, evidence exists that shows that AI will assist in better understanding the climate change phenomenon as well as modelling the impacts thereof (Vinuesa et al., 2020); however, this will not be possible in situations where DT distribution is already uneven between rich and developing countries (WHO, 2019).

Duan et al. (2019) advocate for governments worldwide to develop relevant policies that will be a reference point in the use of AI to avoid unintended negative consequences on society. This assertion further highlights the fear which has gripped both the scientific community and the general population regarding AI. In this sense, it may be constructive to synthesise the prospects involving AI and DTs as a kind of balancing act whereby their perceived potential risks are juxtaposed against their current and future capacity to mitigate climate-related risks, i.e., through enhanced options for climate change adaptation, disaster risk reduction, preparedness, wildfire prediction and prevention (Dehaene et al., 2017, Huntingford et al., 2019, Sayad et al., 2019, Sun et al., 2020, Luetz and Rumsey, 2021, Zhao et al., 2020).

5. Conclusions

This research has tried to analyse the connections between AI and climate change adaptation. One of the main findings from the study is that respondents from North America and South America are already extensively applying and utilising DTs and AI as tools to increase climate change adaptation. This was evidenced by the high levels of optimism as indicated by 80 % of respondents from North America and 75 % from South America agreeing that these tools are essential hence being frequently used. These positions from the two continents can be attributed to the availability of appropriate infrastructure that facilitates the use and deployment of such technologies. However, the situation was different for African respondents, where some respondents indicated that they seldom use DTs or AI as part of their climate adaptation tools box. Thus, the lack of enthusiasm in applying DTs and AI in dealing with climate change adaptation in Africa may be a result of the lack of the required infrastructure to deploy these technologies. This trend, in turn, offers an opportunity for technology developers to provide additional support to African countries, so as to bridge the technology gap.

The study has also identified the fact that there is still considerable fear about the potential risks posed by AI concerning humanity, as some respondents felt that AI is an existential threat to humanity. Others felt that they fear that robots might take their job. Also, some respondents expressed some concerns regarding the potential intrusion on privacy that comes from the deployment of AI, mainly if left unregulated and unchecked. Third trend shows the need to set up suitable legal-ethical frameworks that may regulate the use of AI across different spheres as a whole, and their use in a climate change context in particular.

Furthermore, besides the fear of AI's negative consequences on humanity, our study established that 44 % still believe that AI can be a vital tool in teaching and in research, enhancing climate resilience, and supporting the post-COVID-19 recovery process. Our study also ascertained that from the respondent's views, DTs were also valuable tools that can be deployed towards supporting research on issues related to climate change adaptation and the implementation of SDG13. Our study also further established that DTs can also enhance governance and policy coherence in climate change response and adaptation.

This paper has some limitations. The first one is that the literature review contains relatively recent data since AI is a topic that has evolved over the past few years. A second limitation is the sampling since only 104 people from 51 countries took part in it.

However, despite the limitations, the study provides a welcome addition to the literature. It explores the connections between AI and climate change and offers a rough profile of how it is being practised in various countries.

The implications of this paper are two-fold. Firstly, it sheds some light on the extent to which the literature reports on the connections between AI and climate change. Secondly, by means of the survey, it describes some pressing issues connected with AI, especially its contribution to strengthen governance practices and policy coherence in climate change, and the need to keep the public well informed, with full transparency and accountability.

As breakthroughs continue to be made in various fields of AI and DTs, practitioners in climate change can take advantage of these developments and deploy AI more systematically, taking better advantage of its potential to support increased climate change adaptation. Furthermore, in future studies, comprehensive research on the use of AI for mitigating climate change can be performed to analyse and predict measures to reduce carbon emissions to stabilise the climate. Overall, provided that due care is taken, the use of AI can provide a welcome support to global efforts to better understand and handle the many challenges associated with a changing climate.

Appendix: Systemic Literature Review: Data Matrix

Study	Theme	Category: Climate Change Mitigation (M) or Adaptation (A)	Main Area: (1 = Global or Earth Related; 2= City or Urban Related; 3= Disaster Response; 4 = Water-related Issues; 5 = Agricultural, Land or Tree; 6 = Energy; 7 = Wildfire; 8 = Specific AI Technique	AI Application/Short description	Implications	References
1	Earth Systemrelated measurements to provide automated warnings	A	1	Earth System-related measurements and high spatial and temporal resolution Earth System Model (ESM) to provide automated warnings and advice to society of approaching weather extremes	Better monitoring of climate dynamics	Huntingford et al. (2019)
2	Impact of largescale urbanisation under climate change scenarios on local climate	A	2	Projected land-use data from satellite imagery with dynamic simulation land use results in the Weather Research and Forecasting model to predict scenarios (WRF).	Prediction of future urbanisation under climate change for city planning and action plans reduces human health vulnerability to excessive heat in Pearl River Delta.	Yeung et al. (2020)

3	Mapping of landslide susceptibility for preventing and combating the landslides	A	5	Artificial intelligence methods composed of support vector machines (SVM), artificial neural networks (ANN), logistic regression (LR), and reduced error-pruning tree (REPT) in the development of models for landslide susceptibility	SVM method found helpful in developing an accurate and robust landslide prediction model in the case of Vietnam	Van Phong et al. (2019)
4	Integrated Valuation of Eco-Services and Tradeoffs (InVEST) model to quantify aquatic ecosystem services.	A	4	General circulation models (GCMs) and representative concentration pathways (RCPs) were selected to estimate hydrologic ecosystem services.	Revealing annual and monthly hotspot spatial changes of hydrologic ecosystem services in Taiwan under climate change.	Peng et al. (2019)
5	Blockchain with Artificial Intelligence for managing water utilisation (editorial for a special issue)	A	4	Using blockchain technology for decentralised, immutable public water transactions records to unveil complex patterns in big data on shifting water distribution	Technology integration yields advantages in efficient water abundance and scarcity pattern identification under climate change	Lin et al. (2018)
6	Artificial Neural Network application	A	4	Application of an Artificial Neural Network (ANN). The Backpropagation Neural Network (BPNN) algorithm to forecast rainfall.	Building model to predict extreme rainfall in Indonesia	Hardwinarto and Aipassa (2015)

7	AI for Disaster Response	A	3	Combines climatological and demographic indicators to determine the populations which are most impacted and in need of relief. The tool can calculate the quantity of relief (food, shelter) required	Assists relief organisations in responding effectively	Omdena and WFP (2020)
8	AIDR - Artificial Intelligence for Digital Response	A	4	Analyses tweets (using AI) to detect floods, their location, timing, causes, and impact, which can consequently help disaster relief organisations to respond.	Shortens time required to respond by relief organisations	Imran et al. (2014)
9	Machine learning for agricultural yield prediction	A	3	The model predicts corn yield under climate change scenarios using machine learning algorithms	Can assist in preparing and adapting crop yield to climate change	Crane-Droesch (2018)
10	Machine learning for adaptation policy	A	8	Proposes machine learning to examine the large volumes of adaptation policy documents in various sectors	Helps in streamlining existing adaptation policies	Biesbroek et al. (2020)
11	Machine learning to assess vulnerability	A	5	Developed a mobile application to assess the vulnerability of agricultural communities using machine learning based on weather/biophysical and socioeconomic data	Monitoring of vulnerability and planning interventions	Jakariya et al. (2020)

12	PulseSatellite	A	4	Enables identification of refugee shelters and mapping of floods using satellite images	Helps in the coordination of humanitarian efforts	Logar at al. (2020)
13	Smart irrigation management	A	4	Predicts the irrigation requirements using sensed soil parameters and data on environment and weather from the internet.	Helps in the sustainable management of water	Goap et al. (2018)
14	IoT-Based Smart Tree Management	A	2	Uses internet of things based data to monitor characteristics (air quality, sunlight level, sound pollution level) and health of trees	Can assist in planning afforestation programs and green cities	Shabandri et al. (2020)
15	AI for coral conservation	A	1	Image analysis using Artificial Intelligence (AI) to monitor the health of coral reefs across multiple locations around the globe	Evaluate the adverse effects of climate change on corals	Nunes et al. (2020)
16	AI for Wildfire Evacuations	A	7	Integrates AI with existing wildfire evacuation models for improved accuracy	Can ensure the safety of communities in wildfire-prone regions	Zhao et al. (2020)
17	Machine Learning (ML) methods for wildfire susceptibility mapping	A	7	The case study appraises the potential of various machine learning (ML) methods for wildfire susceptibility mapping in Amol County	A comparative analysis between machine learning applications supports accurate wildfire susceptibility assessments	Gholamnia et al. (2020)

18	Monitoring, predicting and preventing wildfires using several Artificial Intelligence techniques	A	7	The study combines Big Data, Remote Sensing and Data Mining algorithms to process satellite images and extract insights to predict the occurrence of wildfires and avoid such disasters.	The study presents a methodology for predicting the occurrence of wildfires.	Sayad et al. (2019)
19	Machine-learning algorithms to model human-caused wildfire occurrence	A	7	The case study uses ML within the context of fire risk prediction, and humaninduced wildfires in Spain	Results suggest that the use of ML algorithms leads to improvements in prediction accuracy	Rodrigues and de la Riva (2014)
20	Synopsis of the Risk-Reduction Strategies for Floods and Droughts	A	4	The study reviews 150 peerreviewed journal publications from the last twenty years focusing on risk-reduction strategies for floods and droughts.	The AI and the internet of things (IoT) are foreseen to impact future disaster risk reduction	Yang and Liu (2020)
21	Near real-time identification of bushfire impact	A	7	Applying the U-Net deep learning framework to train the recent and historical satellite data leads to an effective pre-trained segmentation model of burnt and non-burnt areas.	More timely emergency response, successful hazard reduction, and evacuation planning during severe bushfire events.	Lee et al. (2020)

22	Flood Prediction Using Machine Learning (ML) Models: Literature Review	A	4	The study demonstrates the state of the art of ML models in flood prediction	Hydrologists and climate scientists can use the survey to identify the best ML methods	Mosavi et al. (2018)
23	Applications of artificial intelligence for disaster management	A	3	Provides an overview of current applications of AI in disaster management during its four phases: mitigation, preparedness, response, and recovery.	Most AI applications focus on the disaster response phase. However, this study also identifies challenges for future research.	Sun et al. (2020)
24	Anticipatory climate change management through early warning (EW.)	A	3	The case study field tests a semi-autonomous analysis of early warning data in the context of humanitarian disaster response	The application of effective semiautonomous EW safeguards humanitarian development gains	Luetz and Rumsey (2021)
25	Machine learning and artificial intelligence to aid climate change research and preparedness	A	8	The study suggests a parallel emphasis on utilising ML and AI to understand and capitalise far more on existing data and simulations	Artificial intelligence (AI) provides enhanced warnings of approaching weather features, including extreme events	Huntingford et al. (2019)

26	AI and responding to the impacts of climate change in the context of the helping professions – e.g. Clinical Virtual Reality tools to advance the prevention, assessment, and treatment of PTSD	A	8	Virtual Reality (VR): A clinical tool to assess, prevent, and treat posttraumatic stress disorder (PTSD)	Advances of AI automation on psychology and mental health care as corollary effect of climate change adaptation on the helping professions	Rizzo and Shillin (2017)
27	European Union Strategies for Adaptation to Climate Change with the Mayors Adapt Initiative by Self-Organising Maps	A	8	Application of artificial neural networks to classify and understand the local climate adaptation measures, verify their differences between themselves, and identify and characterise patterns in the different adaptation strategies examined.	Providing valuable information for its interpretation and the planning of climate change adaptation actions	Abarca-Alvarez et al. (2019)
28	Machine Learning for Conservation Planning under a Changing Climate	A	7	Four machine learning algorithms served to locate the current sites of wildlife habitats and predict suitable future places where wildlife would possibly relocate to, depending on the climate	Localisation of areas of habitat for an exemplary species, based on current climate conditions and pinpointed locations of future habitat	Fernandes et al. (2020)

				change impacts, based on a timeframe of scientifically backed temperature-increase estimates.	based on climate projections	
29	Artificial intelligence and sustainable development	A	1	Discusses the role of AI for three case studies in accelerating the progress on the United Nations (UN.) Sustainable Development Goals (SDGs)	It provides guidelines to management education and the business of leading corporations amid rapid technological and social change.	Goralski and Tan (2020)
30	Renewable energy: Present research and future scope of Artificial Intelligence	M	6	It summarises the review of reviews and the state-of-theart research outcomes related to renewable energy alternatives. Remarkably, the role of single and hybrid AI approaches in the research and development of these RE.	It discusses how Artificial Intelligence could assist in achieving the future goals of the RE.	Jha et al. (2017)
31	Machine Learning to Evaluate Impacts of Flood Protection in Bangladesh, 1983-2014	A	4	it implements machinelearning approaches to study the long-term impacts of flood protection in Bangladesh	Implications for planning for future and more extreme climate futures and global investments in climate-resilient infrastructure to	Manandhar et al. (2020)

					create positive social impacts	
32	Foreseeing global patterns of longterm climate change from shortterm simulations through machine learning	A	8	It introduces a machine learning approach that utilises a dataset of available climate model runs to understand the relationships between short-term and longterm temperature responses under different climate scenarios.	Better data for decision making and identified challenges and opportunities for data-driven climate modelling	Mansfield et al. (2020)
33	Forecasting energy demand, wind generation and carbon dioxide emissions in Ireland using evolutionary neural networks	M	6	Robust evolutionary optimisation algorithm and covariance matrix adaptation evolutionary strategy: Training of neural networks to predict short term power demand, wind power generation, and carbon dioxide intensity levels in Ireland.	The algorithm performs very competitively when compared to other states of the art prediction methods when forecasting.	Mason et al. (2018)

34	Machine learning application in geographically differentiated climate change mitigation in urban areas	M	2	A systematic review of applied machine learning researches relevant to climate change mitigation focused on remote sensing, urban transportation, and buildings.	Big data and machine learning methods emergence enabling climate solution research to overcome generic recommendations and provide policy solutions	Milojevic-Dupont, and Creutzig (2021)
35	Modelling climate change impact on wind power resources using adaptive neurofuzzy inference system	M	8	An adaptive neuro-fuzzy inference system (ANFIS)based post-processing technique is used to consider the spatial variation of wind power density at the turbine hub height and its variability under future climatic scenarios.	Climate change does not notably affect the wind climate over the study area; the real potential of wind power in the area is lower than that projected in the RCM.	Nabipour et al. (2020)
36	Machine learning approaches for spatial modeling of agricultural droughts in the southeast region of Queensland, Australia.	A	5	It aims to develop new approaches to map agricultural drought hazards with state-of-the-art machine learning models.	Such machine-learning approaches can construct an overall risk map, thus adopting robust drought contingency planning measures.	Rahmati et al. (2020)

37	Consistent Climate Scenarios: projecting representative future daily climate from global climate models based on historical climate data	A	8	It compares several techniques (including machine learning algorithms) for modeling climate data requirements for climate adaptation studies in Australia.	Two machine learning models had a good performance. These and other remaining models were used to develop the CCS projections data.	Ricketts et al. (2013)
38	Artificial Intelligence and Climate Change	A	8	it argues for the enhanced use of AI to address climate change and analyses critical policy tradeoffs associated with the increased use of AI.	"Climate change is too important not to try."	Stein (2020)
39	Deep learning to represent subgrid processes in climate models	A	8	It trains a deep neural network to represent all atmospheric subgrid processes in a climate model by learning from a multiscale model in which convection is treated explicitly.	Deep learning can capture many advantages of cloudresolving modelling at a fraction of the computational cost.	Rasp et al. (2018)

40	Accelerating climate-resilient plant breeding by applying nextgeneration artificial intelligence	A	8	Genomics and phenomics integration to speed the development of climateresilient crops, combined with AI, to survey and classify omics data. In addition, socalled "next-generation AI" is expected to change the dynamics of how experiments are planned, thus enabling better data integration, analysis, and interpretation.	AI/ML models to support the development of stress-tolerant crops	Harfouche et al. (2019)
41	Application of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems	A	8	The potential of Artificial Intelligence to leverage big data, which is now becoming easily accessible through using Unmanned Aircraft Systems (UAS) to improve the resiliency and efficiency of production systems (focus on remote sensing tech.)	Developing climateresilient cropping systems	Jung et al. (2021)
42	Determining the best drought tolerance indices using artificial neural network	A	5	Wheat production forecasting through artificial neural networks (ANN) and investigating contributing factors of crop yields	AI/ML models to support the development of stress-tolerant crops	Etminan et al. (2019)

	(ANN): Insight into the application of intelligent agriculture in agronomy and plant breeding					
43	Classification of Crop Tolerance to Heat and Drought—A Deep Convolutional Neural Networks Approach	A	5	Present an unsupervised approach to classify corn hybrids as either tolerant or susceptible to drought, heat stresses, and combination. As a result, the DCNN was recognised as one of the 2019 Syngenta Crop Challenge winners. Products labelled 121 hybrids as droughttolerant, 193 as heat tolerant and 29 as tolerant to both stresses.	AI/ML models to support the development of stress-tolerant crops; prevent yield loss.	Khaki et al. (2019)
44	Applying artificial intelligence modelling to optimise green-roof irrigation	M	4	An artificial neural network (ANN) and fuzzy logic simulated changes in soil moisture; real-time weather data trained the model to predict soil moisture content accurately, and the new model maintained adequate soil moisture content whilst saving 20% water use.	Improve green roof irrigation	Tsang and Jim (2016)

45	Citrus rootstock evaluation utilising UAV-based remote sensing and artificial intelligence	A	5	A UAV-based high-throughput technique was developed for the citrus tree. Phenotypic characteristics of sweet orange trees grafted on 25 rootstocks were evaluated. Data collected by UAV were correlated significantly with manually collected data.	AI/ML models to support the development of stress-tolerant crops	Ampatzidis et al. (2019)
46	Machine Learning for High-Throughput Stress Phenotyping in Plants	A	5	ML tools (SVM, ANN) for plant stress analytics.	AI/ML models to support the development of stress-tolerant crops	Singh et al. (2016)
47	Re-engineering traditional urban water management practices with intelligent metering and informatics	A	4	The intelligent system demonstrated various urban water management practices, including an intelligent system for autonomous water end-use disaggregation and demand forecasting.	AI/ML models for water systems management (efficient supply and demand management)	Nguyen et al. (2018)

48	Intelligent urban water infrastructure management	A	4	DSS for water distribution networks (near real-time logger data providing pressures, flows and tank levels at selected points throughout the system). Furthermore, urban drainage systems and the utilisation of rainfall data predict the flooding of urban areas in real-time.	AI/ML models for water systems management (efficient supply and demand management)	Savic et al. (2013)

49	Improving Urban Water Security through Pipe-Break Prediction Models: Machine Learning or Survival Analysis	A	4	Two leading statistical pipebreak modelling methods: machine-learning and survival-analysis algorithms, are studied. A gradientboosting decision tree machine-learning model and a Weibull proportional hazard survival-analysis model are used to predict time to next break for cast-iron pipes in a central Canadian water distribution system.	AI/ML models for water systems management (efficient supply and demand management)	Snider and McBean (2020)

50	Medium-Term City Water Demand Forecasting with Limited Data through an Ensemble Wavelet–Bootstrap Machine-Learning Approach	A	4	The study explores a hybrid wavelet–bootstrap–artificial neural network (WBANN) modelling approach for oneweek and one to two-month) city water demand forecasting in situations with limited data availability. Models showed to be effective in assessing the uncertainty associated with water demand forecasts in terms of confidence bands, which is helpful in operational water demand forecasting.	AI/ML models for water systems management (efficient supply and demand management)	Tiwari and Adamowski (2015)

51	Applying Artificial Intelligence to Improve Resilience and Preparedness Against the Negative Impacts of Flood Events	A	4	Several ML models are developed and evaluated for classifying floods, i.e., flash floods, lakeshore floods, based on the weather forecast. The results show that the Random Forest technique provides the highest classification accuracy, followed by the J48 decision tree and Lazy methods.	AI/ML models for flood forecasting and management	Saravi at al. (2019)

52	Detection of the State of the Climate System via Artificial Intelligence to Improve Seasonal Forecasts and Inform Reservoir Operations	A	4	AI-based production of seasonal hydrologic forecasts. Multiple global climate signals and assessment of their value on operational decisions. Detected teleconnections and other observed preseason SST anomalies are used to forecast local meteorological variables on a seasonal time scale.	AI/ML models for water reservoir management	Giuliani et al. (2019)
53	Forecasting of daily water level with wavelet decomposition and artificial intelligence techniques	A	4	The study applies wavelet decomposition theory to ANN and ANFIS. As a result, WANN and WANFIS models produce better efficiency than ANN and ANFIS models. Wavelet decomposition improves the accuracy of ANN and ANFIS.	AI/ML for reliable water level forecasting for reservoir inflow	Seo et al. (2015)
54	Hybrid models to improve the monthly river flow prediction: Integrating artificial intelligence and non-linear time series models	A	5	Artificial neural networks, multivariate adaptive regression splines, random forests and non-linear time series models integrated to improve the monthly river flow prediction.	AI/ML for reliable river flow prediction	Fathian et al. (2019)

55	The digital twin of Zurich city planning	A	2	Digital twin for urban planning, with a focus on CC adaptation measures	AI/ML and digital twins for CC forecasting and adaptation and planning	Schrotter and Hürzeler (2020)
56	The European Union builds 'digital twin' of Earth to hone climate forecasts	A	1	European Union is finalising plans for an ambitious "digital twin" of planet Earth that would simulate the atmosphere, ocean, ice, and land with unrivalled precision, providing forecasts of floods, droughts, and fires from days to years in advance.	AI/ML and digital twins for CC forecasting and adaptation and planning	Voosen (2020)

Appendix 2: The survey instrument

1. Gender
2. Age
3. Country of residence
4. Position
5. Average monthly Income
6. Where have you mainly carried out your project/research? (select all that apply)
7. What is your climate change research oriented towards? (select all that apply) 8. How do you relate the relevance of digital technologies and AI to your current work on climate change?

9. How do you regard the relevance of digital technologies and AI to your national/international cooperation in projects today?

10. Which barriers prevent you from taking advantage of digital technologies and AI as part of your climate change work? (Multiple answers possible)

11. The relevance of digital technologies for climate change management in the coming 10 years will

12. The relevance of AI for climate change management in the coming 10 years will

13. In which areas do you see a promising use of digital technologies and AI on a climate change context? (Multiple answers possible)

14. To which extent do you agree with the following sentences:

[Digital technologies and AI can strengthen governance practices and policy coherence in climate change]

[The implementation of timely and properly designed digitally-based technologies and AI can deliver economic and environmental benefits in climate change management]

[Digital technologies and AI can strengthen environmental sustainability and reduce climate vulnerability]

[I fear the possible risks that digital technologies and AI can bring to mankind (e.g. algorithms robots making decisions)]

[I fear the possible risks that digital technologies and AI can bring to employment (e.g. human redundancy)]

[Digital technologies and AI may help to mitigate the inequalities that are being exacerbated by climate change]

[Limitations in digital connectivity disproportionately affects developing countries]

[Leveraging digital technologies and AI may facilitate teaching and research on matters related to climate change]

[Leveraging digital technologies and AI may accelerate progress towards the implementation of SDG13 (climate action)]

[There is need to improve the sustainability dimension of teleworking, remote learning and virtual living to foster education on matters related to climate change]

[There a need to keep the public well informed, with full transparency and accountability]

[Digitalisation and AI will be deployed much faster and on a wider scale than in the past]

[The use of digitalisation and AI need to be paralled by privacy and data protection procedures]

[Enhancing the use of digital technologies and AI will be critical for a climate resilient and sustainable COVID-19 pandemic recovery]

15. Does your organisation plan to increase expenditure on digitalisation for climate change management?

16. Does your organisation plan to increase expenditure on AI for climate change management?

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