A Systematic Mapping of Artificial Intelligence Solutions for Sustainability Challenges in Latin America and the Caribbean

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***Abstract*—The environmental health of Latin America and the Caribbean (LAC) is crucial to the survival of the planet. LAC countries occupy 13% of the Earth's landmass yet contain 60% of the terrestrial life. The region is particularly brittle as climate change looms on the horizon, and its economic reliance on exploiting natural resources is accelerating its biodiversity loss. Central to these problems is that LAC is the most economically unequal region globally. Thus, it faces unique challenges in promoting sustainable development. This paper explores whether and how Artificial Intelligence (AI) may provide methods to accelerate the changes needed to increase resilience and facilitate adaptation. Starting with a systematic mapping of the research on AI for sustainability in LAC, we present a diagnosis of the current situation structured along the proposed axes of climate change, human vulnerability, and biodiversity. Then, we give some illustrative examples of potential directions for further work with applicability to the region. Due to its often overlooked resources, capabilities, and particularly fragile geolocation, LAC is called to play an oversize role in the planet's sustainability in the coming decades.**

***Index Terms*—Artificial Intelligence, Deep Learning, Climate Change, Sustainability, Biodiversity, Human Vulnerability.**

I. Introduction

The Latin American and Caribbean (LAC) region is characterized by its cultural richness, wide ecological diversity, and various climates. Its geographical location covering from the northern border of Mexico to the southern point of Chile has given rise to 11 major biomes that include moist, dry, coniferous, and temperate forests, as well as savannas, pampas, wetlands, montane, Mediterranean climate regions, deserts, and mangroves [1]. The complexity of these environments has been the cradle of diverse cultures now stewarded by the slightly above 660 million inhabitants [2] of the region. For instance, consider that beyond European languages such as Spanish, Portuguese, and pockets of English, French, and Dutch, there is a great variety of Amerindian languages, *e.g.*, just in Mexico, its government recognizes the existence of 64 national languages [3]. With 13% of the Earth's surface, LAC holds 40% of the world's biodiversity [4] with around 60% of the terrestrial life on Earth [5]. Out of the 17 global megadiverse countries, six are in LAC. At the same time, LAC is particularly vulnerable to the effects of climate change, in the form of frequent and devastating extreme weather events [6]. This situation could be perceived as unfair to the extent that LAC contributes relatively little to the problem of greenhouse gas (GHG) generation but receives significant impacts from the global rise in temperatures. LAC is, arguably, one of the most underdeveloped regions. Therefore, it faces a dual challenge of overcoming human vulnerability challenges and doing so in a sustainable form [7].

The concept of sustainable Artificial Intelligence (AI) [8], the blending of AI *for* sustainability and the sustainability *of* AI has made in-roads due to two important factors. For once, there is a pressing urgency to ensure a sustainable future for humankind, understanding sustainability as the ability to meet the present needs without compromising the needs of future generations [9]. On the other hand, Artificial Intelligence (AI), the set of automation technologies capable of perceiving, projecting, and acting independently of human input, has drawn the attention of researchers and engineers in light of more powerful computers and advances in algorithms [10]. Powerful AI primitives have attracted researchers aiming to use advanced technologies to more rapidly reach the United Nations (UN) Sustainable Development Goals [11], improve public policy [12] and decision-making [13], enhance agriculture yield [14], redraw business practices [15], optimize energy production, transmission and consumption [16], and solve logistic [17] and supply chain anomalies [18].

Despite abundant studies on the intersection of AI and sustainability applied globally (see Table I), LAC has received less attention from the AI and sustainability research community. Given the diversity, fragility, extent, richness, and complexity of LAC, there is a need to explore the use of AI to support a sustainable future.

This paper contributes by introducing a systematic mapping of the extent to which LAC has benefited and what opportunities remain open for employing AI techniques to enhance sustainability. Our mapping closely follows the widely respected format proposed by Petersen *et al.* [19] for systematics mappings exploring broad research areas that have not developed a highly formalized structure yet, with adaptations to the social and policy goals of climate impacting research, as suggested in [20]. We join the ranks

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TABLE I
QUERY TERMS FOR THE RELATED LITERATURE SEARCH. NOTE THE OUTSTANDING CONTRAST BETWEEN THE NUMBER OF PAPERS WRITTEN GLOBALLY AND THOSE IDENTIFIED WHEN THE SEARCH IS RESTRICTED TO LAC IN SCOPUS AND THE WEB OF SCIENCE (WOS).

ID	Logic Expression	Scopus	WoS
Q_1	("Artificial Intelligence" OR "Machine Learning")	720,522	585,516
Q_2	Q_1 AND ("Sustainability" OR "Sustainable" OR "Environment" OR "Economy" OR "Society")	92,242	84,207
Q_3	Q_1 AND ("Sustainability" OR "Sustainable" OR "Climate Change" OR "Biodiversity" OR "Vulnerability" OR "Environment" OR "Economy" OR "Society")	98,915	88,140
Q_4	Q_1 AND ("Latin America" OR "Caribbean")	249	434
Q_5	Q_2 AND ("Latin America" OR "Caribbean")	72	96
Q_6	Q_3 AND ("Latin America" OR "Caribbean")	84	108

TABLE II
INCLUSION (IN.)/EXCLUSION (EX.) CRITERIA FOR RESEARCH IN THE AI FOR SUSTAINABILITY IN LAC PLANNING PROTOCOL.

ID	Criterion In.	Criterion Ex.	Description
C_1	×		Studies using AI techniques applied for sustainability in LAC.
C_2		×	Studies citing LAC countries in the manuscript text and do not apply AI techniques in them.
C_3		×	Studies without the full text available.
C_4		×	Not peer-reviewed studies, *e.g.*, blogs, newspaper news.
C_5		×	Duplicate publications or from multiple sources.

of Sanchez-Pi *et al.* [21] constructing a narrative focused on LAC issues. Differently, we frame our discussion around the application of AI to prevent, mitigate and adapt to the consequences of biodiversity loss and climate change on the people most vulnerable.

As individuals directly impacted by the evolving climate disaster, we encourage our peers to look at their research and find out what kinds of climate problems they may be well-suited to contribute to. We hope that this study will be read by researchers and engineers who are looking to make an impact, build new companies to deploy climate solutions in the real world, advise existing companies on how to adapt their business practices, and guide local and national governments to implement policies that will improve our future.

The rest of the manuscript is organized as follows: Section II presents a systematic mapping of the employment of AI to support sustainability in LAC. Based on the results unveiled by this review, Section III offers a diagnosis of the current situation of LAC under three axis: Climate Change, Human Vulnerability, and Biodiversity Loss. Section IV gives an overview of the main opportunities for AI applications in the sustainability context. Finally, we conclude the manuscript and discuss the future of sustainability and projections in LAC.

II. SYSTEMATIC MAPPING OF SUSTAINABLE AI IN LAC

Starting with the search terms of economy, society, and environment, the three pillars of sustainability as defined by Mensah [22], we sought appropriate research papers, both geographically unconstrained and limited to LAC (see Table I), and then a detailed inclusion/exclusion criteria for research in the AI for Sustainability in LAC is presented in Table II. We compared the volume of publications on sustainability topics to those related to AI and ML broadly defined. It is important to note that Van Wynsberghe [8] distinguishes between AI for sustainability and the sustainability of AI. While we observe the difference between using AI for improving sustainability and ensuring that AI does not add to climate change, we are interested in both the benefits and the side-effects of AI for sustainability.

There is an outstanding contrast between the number of documents written for global contexts and those which apply to LAC in Scopus and the Web of Science (WoS). Furthermore, following standard guidelines [23], we expanded the terms of our search using appropriate synonymous. As a comparison, we retrieved the results from Scopus (https://www.scopus.com/) and Web of Science (https://www.webofscience.com) article indexing databases.

Using the query results from both sources, we grouped the articles on the employment of AI for sustainability [24], [25] along the lines of biodiversity conservation, climate change effects, and societal vulnerability (see Figure 1):

Biodiversity Conservation: Research in LAC has focused on particular in the study of corals [26]–[30], as well as fishery [31], [32], bears [33], and in general species distribution [34]. Interestingly, Puschel *et al.* [35] discovered an extinct type of Platyrrhini primate who lived in the Caribbean islands, and an ML algorithm was used to explore whether the specimens were arboreal or not.

Climate Change: For LAC, climate-impacting domain publications have included research on the effects of human activity on the marine ecosystems in the Caribbean [36], glaciers changes in Colombia [37], the identification of pine seedlings [38], the evaluation of coastal flooding risk [39], inferring the patterns for hurricane occurrence [40], risk assessment of shallow landslides hazard in Central America [41], the incidence of air quality [42], the opportunities for water research [43], and the clustering of sargassum (a malodorous seaweed that grows in increasingly warming beach waters) from Earth observations [44].

Human Vulnerability: The largest research effort relating to the use of AI and ML in LAC is related to the human condition and its development [45]. This in-

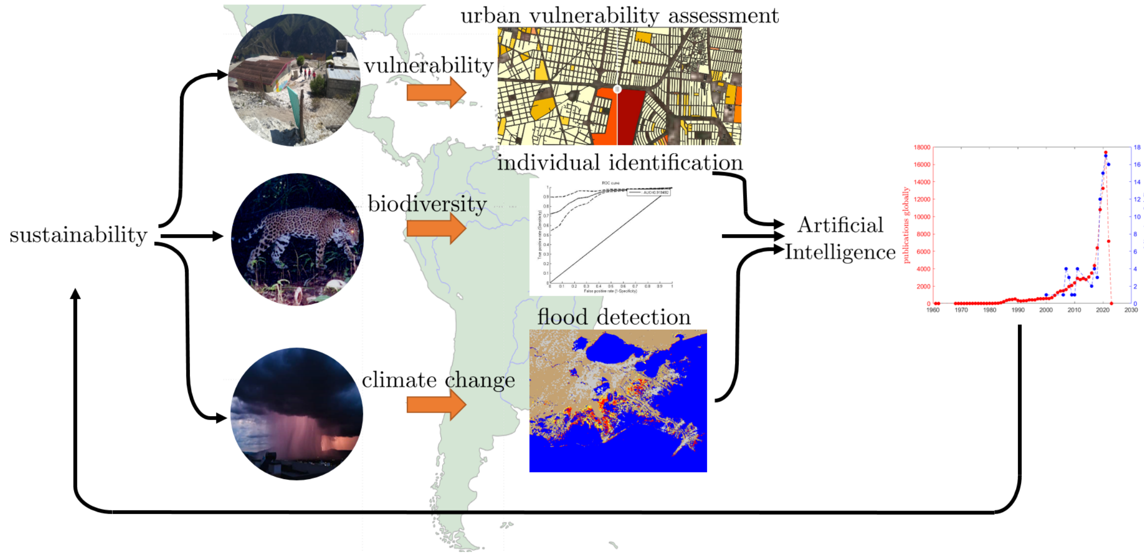


Fig. 1. Sustainable AI. Sustainability may be understood in terms of three pillars: Human vulnerability, biodiversity, and climate change. AI may be a powerful tool to alleviate these issues. This illustration provides corresponding examples for each pillar. The documented application of AI should promote sustainability. A remarkable result of this study is that LAC is underserved relative to other regions worldwide.

cludes structures used to organize communities [46], government [47], [48], and political parties [49] to improve resilience. Health [50], [51] is another topic focus of AI research in LAC in issues including malaria [52], Zika [53] and diseases in general [54]–[56]. There is some emphasize in education [57]–[60] and schools [61], in particular contemporary formats such as e-learning [62]. Education research is particularly important to broader human vulnerability because it can raise income levels [63]. Other research efforts concern the employment of AI and ML in LAC to satisfy energy needs [64], particularly with the use of microgrids [65] to avoid power outages [47]. Additional work considers food needs, in terms of agriculture [66] in general, and some aspects of it, including pollination [67], irrigation [68], and soybeans [69].

While there is a growing interest in LAC to explore the benefits of AI, and its capacity to improve sustainability, we observe that there is much to be done in the area. A discovery of the systematic mapping presented in this paper is that the number of global publications describing the employment of AI for sustainability seems to be three orders of magnitude larger than the those in LAC, pointing out to vast research opportunities in the region (see Figure 2). Another relevant point to consider in the data from Table I is the geographical distribution of studies' authors, topics, and fieldwork. Figure 3 (data and code used to generate the maps at https://tinyurl.com/AI4sustainability) shows the distribution of authors by country in the works found in Table I. Recently, most of the papers on the use of AI for sustainability come from Chinese, Indian and American authors (see Fig. 3a), while those particularly focused on LAC are written by American (Scopus) and South American

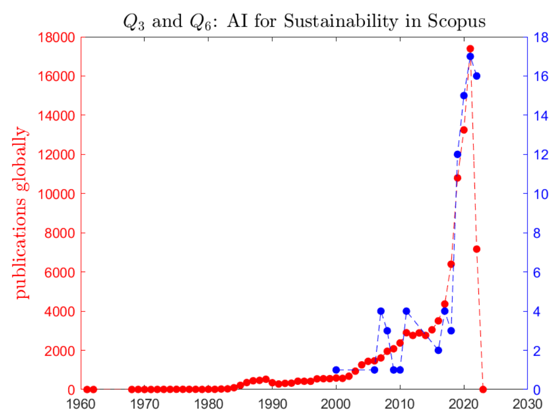
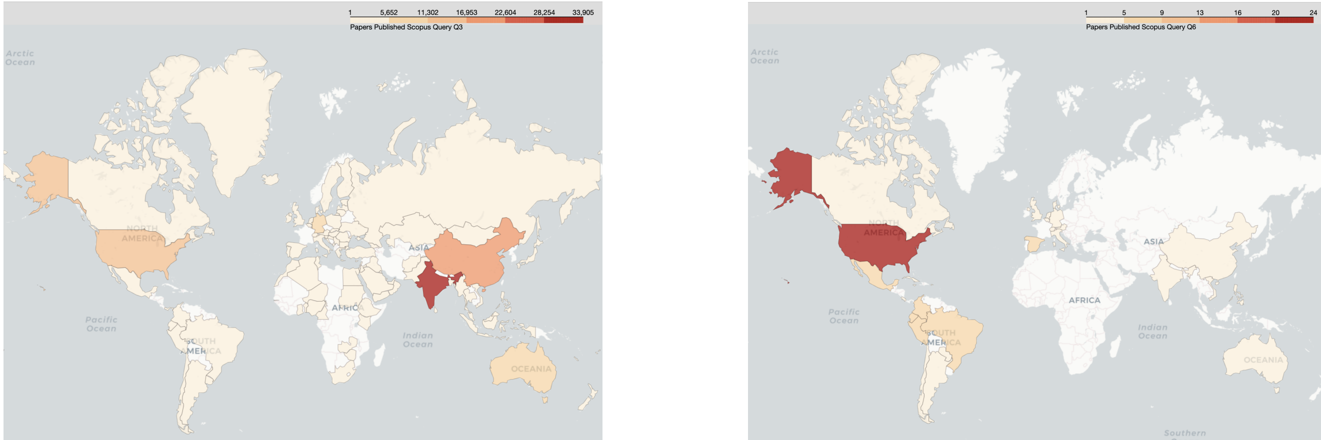


Fig. 2. The employment of AI for Sustainability is gaining interest in the research community. However, the number of global publications dwarfs those generated in LAC by three orders of magnitude, according to the Scopus search engine.

(Scopus) authors, as described in Fig. 3b.

Figure 3 shows that there are fewer studies when including the query with the term LAC (Query Q_6) and lower participation of authors originally belonging to LAC countries in sustainable AI studies (Query Q_3). Despite low publication rates and LAC author participation, the International Science Ranking (https://tinyurl.com/country-ranking, accessed in 06/17/2022) listed LAC countries in prominent positions in the Top-30 countries that published studies about the topic *"AI for Sustainability"* from 1996 to 2021. The important point from our comparison is that even with limited publications, papers involving AI and aimed at sustainability draw significant attention when they involve LAC (Query Q_6).



(a) Authors by Countries from query Q3 in Scopus.

(b) Authors by Countries from query Q6 in Scopus.

Fig. 3. Distribution of the authors by country from Scopus results.

Moving forward in our mapping study, we decided to categorize the studies reviewed into human vulnerability, climate change, and biodiversity loss. This categorical taxonomy distances itself from the economy, society, and environment pillars, shifting attention from anthropocentric factors to nature-related issues. Starting with the core articles unveiled by our systematic search, we perform forward and backward snowball sampling guided by human vulnerability, climate change, and biodiversity mapping.

III. AI FOR SUSTAINABILITY IN LAC

This section assesses the current situation in LAC regarding climate change, human vulnerability, and biodiversity loss. While not comprehensive, it reflects our interpretation of the systematic mapping performed in the previous section.

A. Climate Change

Coping with climate change involves three significant phases: 1) understanding how the climate functions, 2) mitigating the effects of massive greenhouse gas (carbon (CO_2) and methane (CH_4)) emissions, and 3) adapting human society to a rapidly heating planet. Improving LAC's environmental, social, political, and economic stability and growth requires grappling with climate change, now and for the decades to come. In 2021, the Intergovernmental Panel on Climate Change (IPCC) published evidence indicating that because global temperatures have averaged more than 1.1° C above historical trends during the 2010s, it is unlikely that efforts to *mitigate* global warming alone will be enough to counteract the negative consequences of climate change. Governments and people of the world must pursue *adaptation* strategies as well [70].

Despite its diversity of geography and biomes and its much lower contributions to anthropogenic climate change, LAC faces similar adaptation and mitigation challenges as the rest of the world. LAC is already confronting existential threats like the disappearance of Bolivia's Lake Poopó [71] or the desertification of the northeast of Brazil [72]. This subsection maps out domain challenges particularly relevant to LAC and sketches connections between those domains and AI tools that may support their further sustainable development.

The subsections below cover topics important to the Mitigation of Climate Change, Adaptation to Climate Change, and summarize recurring themes in AI for climate action. This section is designed to be an accessible, high-level introduction to AI approaches for climate applications. For a more detailed introduction to domain problems and geographical regions outside LAC, Donti *et al.* and Rolnick *et al.* [73], [74] are extensive surveys that are a good place to start for AI researchers and engineers at any stage of their career.

We have selected our sub-domains of interest in the following way: For the Mitigation sections, the section headers were chosen to be comprehensive with respect to the IPCC Working Group 3 on mitigation [75], with the modification of adding carbon capture. For the Adaptation subsections, we addressed topics covering the areas in IPCC Working Group 2 [76], added Climate Prediction to highlight work on climate science (covering the issues in IPCC Working Group 1 [70] that were most relevant to adaptation), and then added solar geoengineering to cover a proposed high-tech solution topic frequently noted in the popular press. The Finance subsection in the Adaptation section and the topics highlighted in Sec. IV "Opportunities for AI in Latin America" were added to reflect policy, social science, finance, education, and individual action as cross-cutting necessities for implementing climate change mitigation and adaptation. We emphasize that this is not a comprehensive enumeration of all possibly relevant topics but rather a mapping of structurally important issues identified primarily by the IPCC.

1) Mitigation: LAC contributes 8.3% of global greenhouse gas (GHG) emissions relative to North America and Europe (measured in 2014) [77]. Unfortunately, LAC suffers disproportionately from climate change in the form of natural disasters and environmental degradation. Due to weak regional financial infrastructure, LAC is vulnerable to significant economic and social disruption. LAC energy production, especially in Uruguay, Brazil, and Columbia, is greener than in many other places due to hydropower [78]. Reliance on hydropower as a dominant element of the energy matrix leaves the region vulnerable to changes in regional water resources [70]. Moving forward, LAC must continue to mitigate GHG emissions and deploy infrastructure adapted to climate change.

To decrease emissions, the IPCC and world governments have explored significant sources of emissions [79], [80]. Reasonable mitigation solutions have existed for decades [81], so why should the AI community seek new solutions? As climate change continues to affect the world and the practical difficulties of implementing mitigation solutions are met, communities face evolving problems and develop targeted needs for local solutions and participation. This context is where AI and data science become crucial.

a) Energy Systems: The Comisión Económica para América Latina y el Caribe (CEPAL) finds that approximately 46% of LAC emissions are from the energy sector. Coal and oil are already decreasing portions of the energy matrix in LAC, but methane leaks significantly contribute to global warming in the short term [82]. What are the obstacles to converting energy production in LAC to carbon neutral sources?

Besides installing carbon neutral energy sources such as solar, wind, hydro, and nuclear, the significant obstacle is the variability of output from solar and wind sources. Hydropower already represents 63% of Brazil's electricity matrix [83] and wind accounts for 30% of Uruguay's electricity (https://tinyurl.com/uruguay-electricity). The difficulty arises because wind and solar do not provide energy all day or in bad weather, and hydropower is not available everywhere because rivers do not flow in convenient locations determined by urban planning committees. As a result, the demand for electricity and the supply are often misaligned, causing considerable inefficiency and necessitating fossil fuel energy sources that can be run anytime and anywhere. This problem is summarized by the icon *duck curve* graph [84], where the mismatch of renewable supply and consumer demand for the day looks something like the profile of a duck.

To overcome the so-called duck curve, AI can be used to plan when to turn on and off coal and natural gas plants depending on estimated renewable outputs on a timely scale [74]. AI-supported solutions for balancing green power generation can decrease reliance on natural gas (a current successful solution [85]), and such research has already begun in LAC [86].

Forecasting energy supply and demand is a central problem to decarbonizing LAC as energy emissions comprise not only consumer electricity demand but industrial electricity use, electricity for agriculture, and, increasingly, transportation energy in the form of electric vehicles [87]. Well-understood AI techniques can be used in problems that require energy forecasting. These problems include time series modeling of supply and demand, uncertainty estimation for renewable energy generation, and computer vision for estimating energy capacity and emissions as they happen from remote sensing [74]. An even more basic need emerges in addressing the duck curve problem. Vast repositories of heterogeneous data need to be wrangled into convenient datasets for researchers, or new ML approaches need to be developed for low-data settings (https://www.climatechange.ai/dataset-wishlist.pdf).

In addition to integrating renewables into complex power grids, AI has the opportunity to be instrumental in problems related to the ongoing management and operation of the energy sector. Recent literature includes prototypes and real-world case studies of using AI optimization methods and ML for planning optimal power flow of a power grid [88], [89], locations for new hydropower plants [90], and managing existing hydropower infrastructure to prevent disastrous collapses [91]. AI and sophisticated numerical simulations may even contribute to the future roll-out of emerging renewable sources such as off-shore wind power [92], [93] and floating solar [94].

One additional component to an energy system besides generation and operation is storage. Fossil fuels have been the mainstay of the energy sector because they provide energy on demand in any location. Accelerating materials science to discover new electrocatalysts and battery materials is another way that ML can be used to achieve net-zero emissions. For example, the Open Catalyst Project(https://tinyurl.com/ocatproj) seeks to enable researchers to solve hydrogen energy storage via an ML-powered search for novel molecules that can split hydrogen from oxygen in water, thereby creating hydrogen fuel that can directly replace fossil fuels and be transported and used conveniently [95], [96].

Overall, renewable energy increases energy security in LAC [97], if variability can be dealt with. Energy is a significant opportunity for LAC and ML researchers interested in supporting the region.

b) Farms & Forests: Approximately 42% of LAC emissions are from the land-use (19%) and agriculture (23%) sectors from recent CEPAL accounting (http://tinyurl.com/cepal-sustainable). Competent land-use policies and conscientious agricultural practices can preserve the massive carbon sinks (forests and peatlands that absorb emissions) and limit emissions in LAC. However, to take appropriate action, policymakers, engineers, and farmers need to know the sources of emissions and hyper-local environmental attributes of the farmlands or forests they are managing. Often this information does not exist at the scale or resolution required to make adequate plans. AI can help by providing estimations and projections of the necessary information by analyzing large satellite, aerial, or drone imagery datasets. Boilerplate computer vision techniques such as object detection and semantic segmentation could be game-changers for many real applications [98].

Problems in this area that call for AI solutions include the remote sensing of missions [99]–[101], estimation of changing carbon absorption (carbon stock) [102], forest fire detection [103], [104], drought projection [105], and many projects contributing to precision agriculture [106]. AI tools can help practitioners make trade-offs between economic efficiency and environmental resilience [107].

c) Transportation & Industry: Transportation and industrial mining and manufacturing are large sources of emissions, especially in LAC countries with an otherwise *green* energy matrix, like Brazil. Both passenger and freight transport still mostly rely on fossil fuels worldwide. An obvious way to decrease emissions from transportation is to limit transport. AI techniques such as optimization and reinforcement learning can optimize the supply chain for sourcing goods. ML techniques and applications propose clustering techniques for bundling shipments, improving routing, and predicting demand [74]. Recent research indicates that reductions of 10-11% of CO_2 emissions are possible from selecting more eco-friendly routing of cargo in urban delivery [108], a typically high emission context.

To decrease emissions from unavoidable industrial transportation and human commuting, AI can improve how electrical grids respond to the electricity demand of electric vehicles (EV) [109]. EVs are increasingly common worldwide (98% sales increase in 2022), but LAC is slightly behind with only a 77% rise in EV sales. Brazil and Mexico saw 35,000 and 47,000 EVs purchased in 2021. Total market penetration is projected to reach approximately 40% by 2030 (https://tinyurl.com/LAC-electric). This is a fantastic opportunity to decarbonize of one of LAC's largest emitting economic sectors. And one major obstacle, managing the charging grid, can be addressed with AI tools.

d) Buildings & Cities: LAC has a large urban population. Improving the energy usage of large buildings is yet another appealing application of ML to decrease emissions. Smart equipment control for different building systems, such as heating, ventilation, and air conditioning (HVAC), lighting, and simple methods such as identifying insulation improvements, are all projects that AI techniques can help solve. A recent study shows that AI-based control of buildings can reduce emissions by 13-28% [110]. Sophisticated model predictive control of an office building in Belgium shows how advanced AI can make a big difference to a significant source of emissions [111]. Ultimately, using AI to improve buildings and cities saves energy and creates a more comfortable environment for humans to live and work in.

e) Carbon Capture: If GHG emissions are a problem, naïve logic would suggest that removing carbon from the atmosphere is a straightforward solution. Unfortunately for humanity, natural carbon sequestration happens on a geological time scale [87]. ML for materials science accelerate the sequestration process [112], [113]. This area of research touches both foundational ML research and fundamental scientific discovery, an exciting prospect for any researcher, even if the impact on emission mitigation could be decades in the future.

2) Adaptation: As global temperatures rise, effects such as changing weather patterns, flooding, increased occurrence of hurricanes, droughts, wildfire, and degraded environmental conditions due to loss of biodiversity will be increasingly felt in LAC. Adaptation and resiliency may become a more pressing problem for LAC than emissions mitigation, although solutions to the two are deeply intertwined [114], [115]. Adaptation to climate change refers to efforts that change traditional infrastructure and societal organization to account for the effects listed above. The following section provides an overview of domain areas that most need adaptation.

a) Land-use & Agriculture: Earlier discussion detailed how AI can be deployed to mitigate farming and land management emissions. Many of the same technologies can also be used to manage rapidly changing environmental conditions and recommend changes in agricultural practices in a timely fashion [116]. Of principal interest to LAC is degraded water resources. Ground-based measurements of bodies of water have seen a decline since the 1980s, but computer vision and remote sensing may be able to compensate in this low-data regime [117]. Classic deep learning techniques have been used for problems such as river flow estimation [118] and the changing topology of major rivers such as in the Congo River Basin [119]. In the decades to come, AI techniques will be an invaluable resource for monitoring deforestation, identifying eroding wetlands and fisheries, sounding the alarm about drying peatlands that emit vast amounts of sequestered carbon, and at the same time improving crop production.

b) Climate Prediction: The Earth's climate is a complex physical system. Climate modeling is so difficult that the 2021 Nobel Prize in Physics was awarded to pioneers in the field(https://tinyurl.com/nobelcc). Research in AI and climate simulation is an exciting area for advancing our physical understanding of complex dynamical systems and new methods in AI. Climate modeling presents new challenges for the dominant deep learning paradigms where inputs and outputs are strictly constrained, there are no constraints to the form of the learned functions, and learned models are not required to explain how they operate [120]. The entangled spatial, temporal, and spatio-temporal complexities of climate data are prompting the development of physics-informed deep learning [121]. Besides innovation in entirely new ML techniques, classical statistical analysis is being extended for extreme precipitation prediction [122]. Problems that plague individuals and communities like changes in humidity and temperature relationship [123], increasing drought [124], high-frequency flood reporting [125], and precipitation nowcasting [126] are being addressed using extensions of mainstream ML techniques. A boon for scientific discovery is found in the ravages of climate disasters.

c) Solar Geoengineering: In their Sixth Assessment Report: Climate Change 2022, the IPCC decided not to include recommendations for adapting to a warming planet by using solar geoengineering to cool the Earth. This decision is mainly because the effects of solar geoengineering, releasing tiny particles into the atmosphere to change how the Sun's light is reflected, are very difficult to model. It is a risky suggestion to attempt such a drastic course of action without being able to predict the outcome reasonably. ML may be the strongest contender for assessing this promising but potentially dangerous alternative [127].

d) Finance: Economic forecasting has a long history of exploiting ML and statistical techniques. ML offers a possible approach for simulating the complicated effects of carbon taxation and environmental policies. Recent research shows that LAC may suffer significant reductions (9.03–12.7%) in economic productivity over the 2015–2050 period [128]. More detailed estimations would be critical support for governments planning climate adaptation. AI can also be helpful in financial markets, such as deep learning solutions for energy market predictions [129]. A better estimate of renewable energy pricing could decrease volatility in that market and lead to more stable financial opportunities.

3) Recurring themes in AI for climate action: Below are listed the most important themes the authors of this work would want to remind students and researchers entering this field to keep in mind. Please refer to Fig. 4 for a visual diagram of this information and read [73] for a more in-depth taxonomy of the ML research trends at the intersection of AI and climate. In Fig. 4, the connection diagram illustrates the use of six pillars of AI (left side) in major climate-impacting domain areas (right side). The line weights connecting AI topics to climate-impacting topics are proportional to the number of citations identified by Scopus containing the linked issues. This diagram provides a convenient view of what areas of AI research have the most extensive use of the most critical importance in different climate problem areas. It may be helpful to new researchers to use Fig. 4 to identify under-explored connections between AI and climate topics.

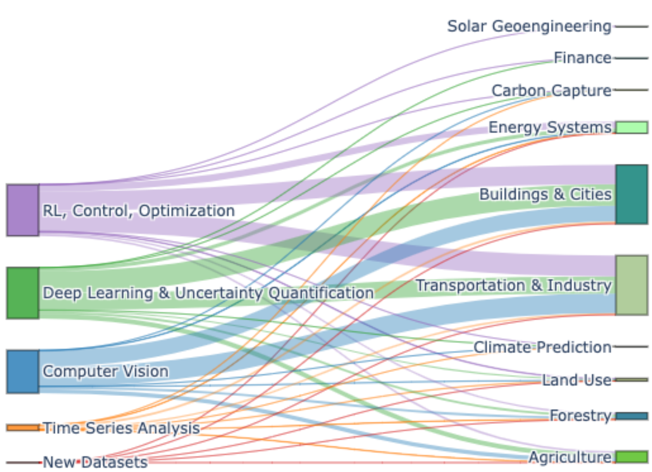


Fig. 4. Connection diagram of the six pillars of AI (left side) in major climate-impacting domain areas (right side).

a) New Datasets: Novel data collection, data mining and homogenization, and data simulation/generation(https://climatechange.ai/dataset-wishlist.pdf). New datasets are essential to almost every climate problem. Adaptation, disaster response, and urban planning are particularly in need.

b) Computer Vision: Remote sensing data is available for many problems, including monitoring emissions, infrastructure conditions, and deforestation [101].

c) Time Series Analysis: Forecasting future events is crucial for fully exploiting solar power, managing extreme weather events, and making the energy and carbon price markets efficient. Predictive maintenance is another crucial need for adaptation. As environmental conditions change drastically due to climate change, infrastructure reliability will be harder to ensure using a legacy estimate of maintenance needs. Hydropower and resilient infrastructure are two areas that would benefit LAC from advances in this area.

d) Deep Learning & Uncertainty Quantification: Approximating time-intensive simulations required for climate predictions and energy systems modeling is a rich area for theoretical breakthroughs. Also, accelerated experimentation for battery material science, electrocatalyst discovery, and carbon capture chemistry may result in new scientific knowledge.

e) Reinforcement Learning, Control, & Optimization: Optimizing systems for precision agriculture and the heating and cooling of buildings requires advances in long-standing fields like control theory and optimization and emerging techniques in reinforcement learning.

LAC has a unique opportunity over the next 30-50 years. Because LAC has less earlier industrialization to overcome, a digitally literate youth, existing hydropower, and geological and ecological advantages, sustainability does not have to be more expensive than in the global North. It may be achieved more efficiently and with less social and environmental pain than in other areas.

B. Human Vulnerability

Though human vulnerability is a fluid concept that includes a myriad of factors [130], some of them addressed by the research community interested in the employment of AI for sustainability. Here, we examine human vulnerability in the light of people's behavior as social entities interacting with a fragile and over-exploited environment.

1) Social Aspects: Even though the proportion of people living with less than \$1.25 USD/day fell from 13% to 4% from 1990 to 2015 [131], LAC remains the most economically unequal region of the world [132]. In response, conditional and unconditional cash transfer and non-contributory pension programs have been implemented by governments covering with social insurance 49.2% of the population in Honduras and 4.3% in Jamaica [131]. Nonetheless, in its last survey, in 2019, CEPAL [133] found that extreme poverty in LAC affected 13.8% of the population while poverty affected 32.1%. Also, the proportion of women without income increased while poverty persisted in rural areas, indigenous people, and children.

Notwithstanding, Stampini *et al.* [134] unveils that despite reducing poverty (for instance, from 46.3% to 29.7% from 2000 to 2013), the LAC population remains largely vulnerable, revealing that there is a significant difference in urban and rural settings and detecting that chronic poverty remains widespread. These characteristics are critical, as Hardoy and Pandiella [135] observe, because there is a strong correlation between risk and poverty. Just consider that the people most at risk of the effects of climate change live and work in poorly conditioned locations; do not have the knowledge and capacity to adapt; and once a disaster occurs, cannot handle the impact.

Of particular interest is the LAC population working in the informal economy, a percentage ranging from 25% in Uruguay to above 80% in Guatemala, Honduras, and Bolivia [136] (about the same as in the pre-pandemic years [137]). Altamirano [138] finds that as far as the social benefits do not reach them, they face growing economic uncertainty. As a result, they establish weaker political liaisons and may not be well represented in decision-making processes. Overall, Rojas [139] states that LAC is characterized by heterogeneous development, exploitation of natural resources, and frequent social movements where inequality and social exclusion are still present.

Regarding health, LAC is the region most devastated by COVID-19 (28.2% of global deaths from only 8.4% of the world's population) [140]. The pandemic has exacerbated the problems related to human health. For instance, Angulo [141] highlights the potential effects of COVID-19 on mental health in the light of the existence in the region of pockets of poverty and socioeconomic vulnerability and inequality, especially among women.

Internet is a powerful tool for conveying information that can be transformed into education, health, and business activities. About 67% of the individuals in LAC have internet usage, being higher in Chile with 82% and lower in Haiti with 12% [142]. Four out of ten persons in rural areas have connectivity and 71% in urban areas [143]. Regarding the quality of the internet service, 46.7% of the LAC population has connectivity through fixed broadband services while 9.9% has access through optical fiber [144].

In LAC, there is high skepticism about an ongoing global climate change, with 44% of the population incredulous of it; out of those who are convinced, 17% do not attribute it to humans as the primary drivers [145]. Interestingly, this may not be the case in female-headed households, and in fact, they seem more resilient to shocks due to climate variability by the diversification and amount of income [146]. Comerón [147] supports this finding. She analyzes the relationship between increased human vulnerability and gender psychological and physical violence, suffered by about 70% of women, and the preeminence of hazards. Comerón emphasizes the need to include gender as a factor to prevent, mitigate and remediate natural risks and their effects. Using this approach may palliate the effects that recurrent disasters (including wars, economic crises, rebellions, or those that originated in nature) have on the reproductive capabilities [148].

2) Environment: LAC is a fragile region that will be most affected by climate change and whose population is dependent on exploiting natural resources. Consider that Puerto Rico and Haiti are two of the three most affected territories or countries by climate-related extreme weather events [6]. Martinez *et al.* [149] provide a historical compilation of the effects of rainfall, rising temperatures, and extreme events associated with the Niño phenomena between 2015 and 2016. At some point, the winds associated with it raised the sea surface temperature by 4°C above average. Rodriguez-Morales [150] observed that this makes it critical to produce human vulnerability and risk maps to climate anomalies as extreme events become more frequent and severe. These events are now so pervasive that they give rise to ecosyndemic exposure or the disease interactions resulting from changes in the environment caused by humans. Ramirez and Lee [151] note that some infectious diseases, including Chagas, chikungunya, dengue, malaria, and zika, heighten during extreme climate events. The situation is problematic as COVID-19 rages through the continent.

In the wake of more frequent extreme weather events, there is the need to elevate awareness, investment, and preparedness. These actions should highlight the relationship between climatological, hydrological, weather events and human well-being. Nagy *et al.* [152] study the occurrence of climate associate disasters and infer the geographical and socioeconomic determinants of human vulnerability. But more importantly, there is the need to bring the studies and analysis about climate change effects and adaptability to decision-makers. Based on eight studies assessing climate change vulnerability, Wood *et al.* [153] identify credibility, prominence, and legitimacy as the critical factors in scientific research needed to affect policy decisions.

These phenomena combined caused a significant effect on agriculture and stressed food security through droughts in Colombia, Venezuela, Brazil, the Caribbean, and Mexico. Some of the people most affected by the environmental risks and vulnerability factors are the indigenous people [154]. In fact, with between 45 and 50 million people, LAC concentrates the world's most significant percentage of the indigenous population. Inescapably, climate change will affect production and food security. Prager *et al.* [155] limit the regions that will improve and those that will face challenges. They studied bean, maize, rice, soybean, and wheat crops and the economic viability of agricultural output through them.

After observing an increase, between Februaries of 2020 and 2021, of 274% of migrants arriving at the US-Mexico border, Rosenthal [156] claims that climate change is already forcing the population, in particular the rural indigenous population of women, to emigrate. Erlick [157] documents that more than three million Guatemalans have left their country for the US because they cannot produce enough food at home.

C. Biodiversity Loss

Life and its diversity are what make planet Earth unique. It is estimated that 8.7 million (± 1.3 SE) species of all kingdoms inhabit the Earth [158], with about eight billion living people sharing the same space. Unfortunately, this coexistence over the centuries has not produced a balanced coexistence. The first Earth Summit, held in Rio de Janeiro, Brazil, in mid-1992, highlighted the importance of conserving, protecting, and restoring the Earth's ecosystems. The Earth Summit participants declared, almost unanimously, that human actions were dismantling the Earth's major ecosystems, wiping out genes, species, and biological materials at an alarming rate.

According to Wojciechowski *et al.* [159], 7 out of 25 priority hotspots for biodiviersity conservation are in LAC. Currently, LAC is the most biodiverse area on Earth. However, despite its biological and ecosystem diversities, habitats in LAC face constant environmental challenges such as deforestation, inappropriate land-use practices, biodiversity loss, groundwater contamination, aquifer depletion, and soil erosion. AI and other advanced technologies can be instrumental in the fight to slow the massive loss of diverse life in LAC. We summarize several significant directions for deploying AI and other technological solutions to mitigate biodiversity loss in the subsections below.

1) Adaptation of Agriculture and Land-use to Preserve Biodiversity: Alpizar*et al.* [160] observed that the relative percentage of protected natural areas in LAC is above the global average. LAC countries have reserved 24.26% and 23.24% of their terrestrial and marine surface, compared to 15.79% and 8.09% for the rest of the world. Alpizar*et al.* also point out that LAC is a pioneer in creating large-scale payments for ecosystem services programs (PES), *e.g.*, Costa Rica's iconic government-led PES program or Mexico's PES program which offers compensation to landowners for environmental stewardship. These actions are necessary because while there is an increasing demand for infrastructure, forests, wetlands, and mangrove ecosystems protect the infrastructure from natural hazards such as landslides and floods.

Agriculture is still one of LAC's most significant income sources, representing 29%, 10.5% and 1.5% of the total Gross Domestic Product (GDP) in low, middle, and high-income countries [161]. However, the expansion of agriculture has been the main driver of the increase in deforestation and land-use changes, creating a dilemma between agribusiness and rainforest preservation. The planted area covers about 38% of the territory of LAC [162] producing about 15% of the global exports [163]. Population growth trends indicate the constant need for food production systems to satisfy this demand. However, climate change threatens the ability to meet this demand. In response to these challenges, adaptations of ecosystem-based practices have proven to effectively combat reduced biodiversity and adapt to climate change in support of farmer livelihoods.

In addition to changing how food is grown and harvested on land, humans will need to adapt how food is harvested from the sea to slow the extinction of oceanic species, decrease coastal erosion, and meet the challenge of rising sea levels in a warming world. In developing nations, like those in LAC and elsewhere in the global South, small-scale fisheries (SSFs) can play an important role in stabilizing food supply, shoring up vulnerable communities' economies, and even protecting natural habitats through contentious sea farming. Challenges for managing SSFs include the wide variety of species harvested, rapidly changing weather patterns, complex ecological interactions, and an enormous land/sea area to monitor. Recent and ongoing efforts to use AI methods to attack these problems have been successful in Mexico [164], where the Baja California Sur fisheries are the third largest in the world, and in Southeast Asia (https://www.climatechange.ai/blog/2022-06-16-grants-mangrove), where an international team is using ML methods to identify an enormous 40,000 hectares of small-scale shrimp fisheries that could be engaged to grow and protect mangrove forests in an effort to increase global mangrove cover by 20% in the next decade. Overall, efforts in small-scale fisheries, possibly aided by AI techniques, could be a crucial tool in fighting climate change caused poverty and biodiversity loss.

The main motivations to restore damaged ecosystems include conserving biodiversity, enhancing ecosystem processes, combating climate change, and providing ecosystem services for cultural and spiritual reasons [165]. Among the possibilities, multi-agent systems techniques may offer substantial leverage in the planning and decision-making of biomes' restoration and monitoring process. As described in Ralha *et al.* [166] a multi-agent system model for monitoring land use, allowing the assessment of areas of urban occupation, pastures, plantations, and native forests of Brazilian Cerrado using Landsat images permitting government managers to draw up policies to improve land use and restoration.

2) Natural Disaster Monitoring and Management: Another contributing factor to the destruction of biodiversity includes natural, criminal, and controlled forest fires. Monitoring and predicting forest fire risk are beneficial and essential areas of study. AI is being used to support the prediction of forest fires [167]. AI tools developed for monitoring and predicting forest conditions can also be used to help combat and control fires before and during these events. Using classifiers based on light-weight Support Vector Machines (SVM), researchers monitoring forest fire risk in Lebanon achieved up to 96% accuracy classifying low- vs. high-risk fire areas in the summer. With the help of these techniques, it is also possible to mitigate the potential risks of fire, using robust estimators and satellite images to assess the amount of accumulation of combustible material in regions of woods and forests that may be sources of forest fires [104].

3) Large-scale Biome Monitoring: Preserving tropical forests and savannah areas reduces the effects of biodiversity loss at LAC. In this case, in addition to advancing the growth of cities, an increase in planting areas reduces illegal deforestation for logging. These actions directly affect the maintenance and survival of biomes and preserve the local biodiversity.

Still, on the issue of flora preservation in LAC, the complexity of the necessary actions grows as the budget made available for the local governments shrinks. In the case of the Amazon, the extent to be monitored is on a continental scale, around $5,015,067$ km^2, in which unoccupied aerial vehicles (UAV) monitoring activities are practically unfeasible. In these cases, it is indispensable to use strategies incorporating AI and remote sensing techniques to monitor changes in the preserved area. Along these lines, Mehdawi *et al.* [168] introduce techniques to monitor changes in the size of the plant biome of interest, using as a basis multi-spectral remote sensing images associated with classifiers built from artificial neural networks, collecting information about changes in the region of interest.

According to Sierra *et al.* [169] efforts in LAC focuses on the process of national representation of their vegetation. This way, the conservation and recovery process becomes viable, mainly due to the hundreds of ecosystems involved and more than 1,000 types of vegetation. Voluntary damages cause devastation to the plants' biodiversity and natural factors such as plant diseases that affect the biomes to be preserved and pose a risk to the food security of the local population.

4) Fundamental Biodiversity Research: The biodiversity loss process involves destroying life at different levels, from genetic material to the functional traits of an ecosystem. One way to preserve information about an ecosystem and perhaps recover lost biodiversity in the future is through the genetic mapping of species. The GENOMA [170] project aims to increase the understanding of species' biology and use AI to contribute to ecosystem recovery. In one example, this project mapped new species of freshwater fish [171] using genetic alignment techniques. In that case, one of the substrates for performing the alignment of multiple sequences of materials uses an iterative method approach called FFT-NS-1 [172]. In this method, the convergence adjustment process uses weight estimators in the search process with artificial neural networks [173].

In this section, we have briefly touched on the vast opportunity to use AI to address complex biodiversity challenges. We believe that while there is dramatic environmental risk in LAC, there is also the chance to pioneer a new relationship between the human and non-human inhabitants of LAC. AI can be a powerful tool for responsible stewardship in LAC.

IV. Opportunities for AI in Latin America and the Caribbean

AI may be considered a double-edged sword with the potential to tackle human vulnerability by increasing productivity and living standards or a disruptive phenomenon that may exacerbate inequality, as described in [174]. In light of the current situation in LAC, there are some exemplary practices taking place which have the potential to foster sustainability. In the section below, we highlight some of these laudable efforts.

A. Adapting to Climate Change

When designing solutions to adapt to climate change, there is the opportunity to improve on what existed before global warming began. We want to highlight two cases where researchers and entrepreneurs have not only developed sustainable solutions but also surpassed what has been possible with high-emission legacy solutions. These timely case studies were selected because they demonstrate a profound key to a problem also faced in LAC. These are not broad examples that cover a significant portion of adaptability concerns. Instead, these are targeted projects on a scale that we imagine attractive to the core audience of this paper.

Precision agriculture is a domain where sustainable solutions can surpass legacy practices. Scientists and engineers affiliated with Microsoft Research India and The Climate Corporation have deployed a solution that combines internet of things (IoT) sensors and multi-scale deep learning encoders to predict hyper-localized soil and crop attributes for small farmers. Kumar *et al.* [175] introduce their DeepMC system and show how deep learning can be used in the real world to improve agricultural output for farmers of limited means. By deploying AI like the DeepMC system, agricultural producers can make themselves both more robust to changing climate and more economically efficient.

From a philosophical perspective, AI is an enabler of new work patterns. Classic AI techniques such as Dijkstra's algorithm and constraint programming have been used for decades to tell drivers the fastest way to their destination. Ride-sharing companies were made possible by 20th-century AI. Those companies may worsen emissions, but their techniques are still precious to adaptation innovations. The Pedal Me mobile app of London (https://pedalme.co.uk/why-cargo-bikes) determines the optimal routing of electric cargo bikes for inner-city package delivery, which is emissions-free and faster than by car. The developers of Pedal Me used the Google OR optimization engine (https://developers.google.com/optimization) and the driving distances from OpenStreetMap (OSMnx https://github.com/gboeing/osmnx). Pedal Me is a clear win for the environment and an excellent startup concept.

Many AI tools, from decision trees to Bayesian optimization, are being investigated to help cope with the complex energy network problems that arise from decarbonizing transportation [176], [177]. Using AI to reduce transportation emissions seems like an easy win, but this is one sector where the Jevons paradox, a famous, non-intuitive problem, can happen. This paradox occurs when an increase in technological efficiency leads to a rise in consumption rate. For example, adding electric cars to a power grid that is not renewable (Mexico) could result in *increased* emissions. Similarly, autonomous vehicles may lead to more driving time and growing emissions. Researchers, engineers, and entrepreneurs need to examine solutions for unintentional downsides like this.

While working to mitigate emissions and adapt to climate change, AI researchers should not worsen emissions. Training and using large-scale ML models causes emissions on an electricity grid that is not entirely renewable. Researchers and engineers should endeavor to limit power use and the related emissions [178]. To improve accountability, there is momentum in the AI community to encourage authors to include a description of how they have limited emissions in their work [179].

B. Alleviating Human Vulnerability

The world has advanced much in the reduction of poverty. Just consider that at the 19th-century onset, 94% and 84% of the population lived in extreme poverty with \$2 and \$1 or less per day in inflation-adjusted American dollars [180]. Thus, while sub-Saharan Africa is the poorest region of the world, LAC is the most unequal [132]. China has been particularly successful in reducing poverty, going from 88% to 0.7% of its population from 1981 to 2015 [181]. Today's reference to poverty in China refers practically to the rural poor. The country has passed through several large-scale poverty alleviation projects starting in 1986 [182], thanks to its rapid growth, to the implementation of the programs that provide food and clothing in underdeveloped areas. These programs relaxed restrictions to provide funding for areas for non-live people (e.g., empty spaces) in counties with high poverty indexes.. By 2011, China identified regions consistently being recognized as poor and developed special programs. In its most recent national program, China is introducing e-commerce in the rural population [183]. The e-commerce program in rural areas permits their economic development through the employment of AI. It introduces internet infrastructure and human resources for e-commerce while identifying the agricultural products supply and marketing information [184]. This situation allows people to make informed decisions about production and sales according to market demand, giving poor people bargaining power [185]. Some people need training, while others can use an e-commerce platform to operate their online stores. It has the additional advantage of providing information from the world outside via the internet and integrating them into the digital age.

LAC has been hit hard by COVID-19, but it is also struck by other preventable diseases that cut off the development of talent, creativity, and entrepreneurship, leaving traces of psychological traumas. That is, in general, the case in most middle and low-income countries as shown by the Service Readiness Index (SRI), an assessment between 0-100% about the readiness of facilities to provide health services developed by Leslie *et al.* in [186]. There, hospitals and health centers ranked 77% and 52% respectively in health facilities for SRI rank. Fleming *et al.* [187] unveil that 47% of the global population has deficient or no access to diagnosis, affecting mainly the poor, rural, and marginalized communities. Nonetheless, it is interesting that international soft-soda producers, while contributing to the obesity crisis, deplete the water supplies and reinforce damaging the environment with the production of plastics, excel at supplying to every corner of the planet. In their logistics [188], they use local supplies, identifying in real-time the location of its units, optimizing routing, delivering products to the sale points directly from the manufacturing facilities, monitoring performance continuously, and embracing innovation. Sargent and Darkoh [189] have applied these characteristics to the treatment of HIV in South Africa, where at some point 38.5% of the adult population tested HIV-positive. Through the prediction of demand, the simulation with digital twins [190], the attention to the needs of individual patients with the support of machine learning algorithms trained with hundreds of thousands of patients, they connected 1200 hospitals to the platform, incorporating 2.4 million cases, about 10% of the world's HIV cases.

C. Tackling Biodiversity Loss

Several strategies are used in tackling the reduction of biodiversity in LAC, including the automatic recognition of the plant species [191]. Andre *et al.* [192] and Al-Hiary *et al.* [193] use deep learning techniques to identify plant species from images, including their most common pathologies. Still, other AI techniques can be valuable and practical in preserving plant biodiversity. One approach to monitoring large areas of dense vegetation is UAV. These devices are integrated with geospatial sensors, including cameras sensible to a broad spectrum of electromagnetic frequencies, which are combined with AI to identify possible degradations in the inspected biome [194].

An important indicator of local biodiversity preservation is the ecosystem's ability to collect and store atmospheric carbon. Large vegetation areas accomplish this task. There is growing concern about the inability of countries to guarantee the maintenance of conservation areas so that the carbon cycle is possible, especially those with large tropical ecosystems such as the Amazon forest in their territory. The Amazon forest has an extensive forest area in nine South American countries, mainly Brazil (69%). The lack of political coordination between countries is a significant risk factor for the entire carbon cycle. To mitigate and minimize damage to the carbon cycle, the initiative by Freitas *et al.* [102] developed an approach for estimating the carbon stock of the Amazon forest. The analysis of laser radar images (LIDAR), combined with an AI strategy, achieved 97% accuracy in estimating indirect carbon stock.

The reduction of plant preservation areas directly influences the decrease of the fauna. The same happens in the degradation of marine preservation areas such as coral reefs and other places inhabited by local fauna, which are subject to the degradation of their environment. The range of opportunities is enormous, with a potential application focusing on land and sea areas, all of them with abundant biodiversity. For these activities, Mehrnejad *et al.* [195]

describes an initiative for the preservation of the marine ecosystem, whether in shallow or deep waters, based on the use of artificial neural network techniques for the detection of stationary animals (large conglomerates of crabs). Similarly, the detection process for large numbers of terrestrial animals can be carried out to allow the monitoring and management of the fauna, directing efforts to improve preserving local biodiversity with AI. For instance, Zhu *et al.* [196] developed a method in which a graph regularized flow attention network (GFAN) to monitor animal counts for agriculture and wildlife preservation.

Another way of preserving biodiversity, or minimizing the process of reducing the biodiversity of a biome or ecosystem, is by monitoring evolving diseases that may occur in the species. Malik *et al.* [197] uses image processing techniques combined with artificial neural networks and K-Nearest-Neighbors for the detection of Epizootic Ulcerative Syndrome (EPU), which affects fish populations in their natural habitat.

For Wang *et al.* [198], the deteriorating water quality leads to the biodiversity crisis, affecting all ecosystems. The proposal presented for water monitoring was based on an approach using AI and the Internet of Things (IoT), making it possible to monitor of water quality in these biomes. Their technique is based on a multivariate polynomial regression model of degree eight, the coefficients of determination results are 0.89, 0.78, 0.87, and 0.81 for chemical parameters nitrate nitrogen(NO3-N), biochemical oxygen demand(BOD5), phosphorus(PO4), and ammonia(NH3-N), respectively, the results are evaluated for the urban river Lam Tsuen in Hong Kong.

According to Lawler *et al.* [199] the COVID-19 pandemic has links to biodiversity loss and ecosystem health. The main effects of COVID-19 on biodiversity loss are diverse and interconnected on conservation funding, tourism, environmental policy, indigenous land managers, and human-wildlife contact. Effects of the reduction in conservation funding, lockdown of people and activities, and rural and low-income populations, are the main factors that directly affect biodiversity and ecosystem health.

D. Improvements in Data Availability and Transparency

AI can improve decision-making processes in climate changes, human vulnerability, and biodiversity loss applications. Regardless of which technique, method, or model is used, these are based on AI, whether supervised or not, in a stochastic or deterministic approach, using deep or superficial learning methods, the need for data availability is fundamental for high-quality and robust results. As obvious as this statement may be, the data available must be reliable, transparent, and as detailed as possible.

An example demonstrating the importance of data availability, transparency, and reliability was how several democratic and authoritarian governments addressed the issue of combating the COVID-19 pandemic. Anaka [200] describes that democratic governments are disadvantaged with the current pandemic mainly because they cannot intervene in their citizens' lives as aggressively as their authoritarian counterparts. Also, suggest that possible data manipulation may account for the apparent advantage of authoritarian countries. And unfortunately, this situation prevented the use of techniques and methods based on AI from being used to improve the results of combating the pandemic, being able to minimize the spread of the virus, reduce the number of hospital admissions for severe cases, and also including in reduction of deaths.

For Lnenicka *et al.* [201] transparency in the public sector data is one of the most important topics of the current debates on accountable, participatory, and good responsive governance. However, in several governments in LAC, democratic or not, regardless of their support and direction of policies for sustainability and preservation of biodiversity, they have restrictions to data access. The barrier is mainly in the absence of open data portals, where data are standardized and made available for the study and analysis of various sectors of action of these governments. In addition to the difficulty of access, several countries maintain databases with incomplete, inaccurate, and improperly organized data.

Even in countries that have open data portals, the difficulty in obtaining information is considerable. Therefore, it is complicated to develop models, methods, and applications using AI. The high cost of acquiring, organizing, and managing these data makes it difficult to develop strategies addressing sustainability issues and derivatives activities. It is a fact that when openly shared, data have their value and may allow the improvement in every sector of society, including those involved in initiatives aimed at sustainability.

Regarding the access and availability of public data, including the relevant data for analyzes involving sustainability and the environment, in 2011, only 12 LAC countries had a government transparency law and access to information legislation [202]. With time and pressure from local and global society, the situation improved. By 2021, LAC had 31 countries with policies and legislation for accessing public government data [203]. Compared to other countries, the LAC country with the best score in the ranking is Uruguay, and occupies the 18th position out of 180 countries analyzed, as presented in [203].

CONCLUSION

With a late arrival on the global scene, America was subject to conquest and subordination. By imposing a political system based on exploiting natural resources and its later abdication to economic powers, manufacturing and technological advances lagged, leaving a trace of economic inequality, social unrest, and a brittle financial situation. Compounding this situation, LAC is in a particularly fragile geographical condition as climate change gives rise to more frequent and devastating extreme weather events. LAC's reliance on natural resources is also threatening its rich ecological in-heritage while impeding it from sharing the wealth generated by the employment of advanced technology.

The recent revolution in AI offers valuable experiences that could help LAC leapfrog its current socio-political and economic environment in a sustainable form. These opportunities for the employment of sustainable AI include evidence-based policymaking, the construction of appropriate infrastructure to empower its citizens, the creation of a governance model based on transparency, openness, and consequences, and the increase, protection, and monitoring of its natural resources. Through these action lines, the LAC leadership may lay the basis for a more resilient future.

In the future, we will explore some of the opportunities revealed by our systematic mapping. For example, we will investigate the use of satellite sensors to assess human vulnerability at a fine-grained level with broad spatial coverage; we will characterize forestry for conservation in protected natural areas; we will estimate the risk of flooding to reduce the effects of extreme weather events; and we will monitor wildlife in the open ocean to understand migratory patterns.

This research has revealed that LAC is very neglected, and there is a need to build decision-making support systems that allow reliable, comprehensive, and flexible monitoring if we want to respond to the challenges of sustainable development. These characteristics are contained in the solutions that artificial intelligence can provide in the significant challenges ahead.

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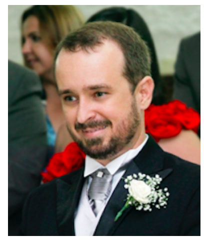

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