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# Climate smart computing: A perspective

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ABSTRACT

Climate change is a societal grand challenge and many nations have signed the Paris Agreement (2015) aiming for net-zero emissions. The computing community has an opportunity to contribute significantly to addressing climate change across all its dimensions, including understanding, resilience, mitigation, and adaptation. Traditional computing methods face major challenges. For example, machine learning is overwhelmed due to non-stationarity (e.g., climate change), data paucity (e.g., rare climate events), the high cost of ground truth collection, and the need to observe natural laws (e.g., conservation of mass). This paper shares a perspective on a range of climate-smart computing challenges and opportunities based on multi-decade scholarly activities and acknowledges the broader societal debate on climate solutions. Moreover, it envisions advancements in computing methods specifically designed to tackle the challenges posed by climate change. It calls for a broad array of computer science strategies and innovations to be developed to address the multifaceted challenges of climate change.

## 1. Introduction

Climate-smart computing aims to help us "understand and analyze the climate ecosystem, build resilience to climate-driven extreme events, and mitigate and adapt to climate change" [1]. Its advanced computing techniques range from smart sensor-based networks to novel climate informatics techniques, such as artificial intelligence (AI). These technologies are crucial for global efforts to mitigate the severe impacts of climate change, which has become the foremost issue confronting the global community. The increasing frequency of extreme events, such as extended heat waves, underscores the urgency of these efforts. Bringing anthropogenic greenhouse gas (GHG) emissions to zero, sometimes referred to as "net zero", is viewed as critical to averting the worst impacts of global warming and climate change. According to the Paris Agreement, signed by over 70 countries, achieving net zero is essential to maintain a livable planet. This commitment is underscored by the global engagement with climate goals and specific pathways to net zero currently being pursued by the United Nations.

Fig. 1 shows the role of GHG removal in climate change mitigation. The left subfigure shows historical and projected GHG emissions over decades, with brown areas representing gross positive $CO_2$ emissions, and light greenish-gray areas showing other GHGs like methane ($CH_4$), nitrous oxide ($N_2O$), and fluorinated gases. The "Business as usual" trajectory indicates rising emissions without intervention, while the "Below 2 °C" pathway highlights the necessary reductions to net zero GHG emissions by reducing gross positive GHG emissions (green areas) and increasing negative emissions (blue areas), which represent activities that actively remove carbon from the atmosphere. The right subfigure categorizes activities associated with these efforts: conventional abatement technologies such as renewable energy, advancements in emitting technologies, and carbon removal technologies,

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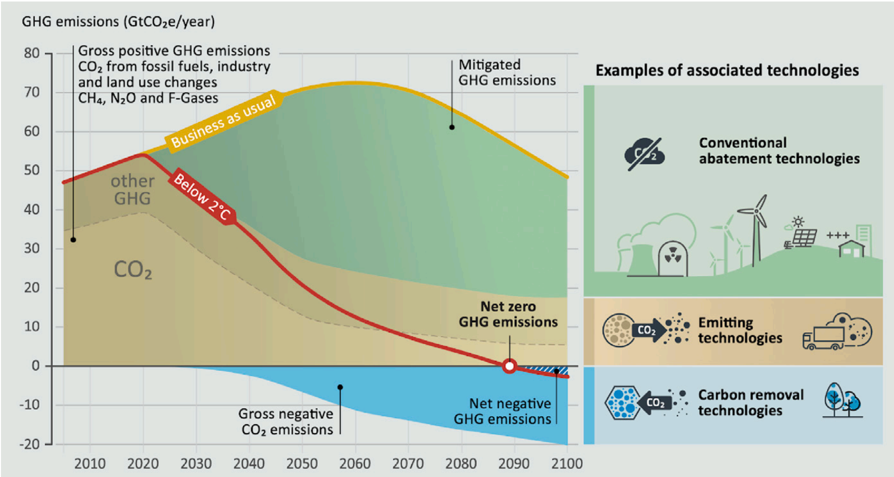



**Fig. 1.** The role of greenhouse gas removal in climate change mitigation [2].

including reforestation. Compared to historical trajectories of net GHG emissions, these emission targets are both ambitious and urgent.

Computing will play a growing role in helping different sectors of the economy work towards net zero. Computing itself generates emissions, however, so it is useful to understand where its emissions come from. Fig. 2 presents the sectors that contribute most to global GHG emissions [2,3], namely energy systems, industry, agriculture, transportation, and buildings. Globally, the energy sector is the largest contributor to anthropogenic GHG emissions, followed by industry and agriculture, although, the importance of these sectors may differ by region. For example, in the U.S., the transportation sector is the largest contributor to anthropogenic GHG emissions [4]. Of particular interest to the computing science community is the information and communications technology (ICT) sector, which contributes approximately 2% of global GHG emissions and 4% of global electricity consumption. Fig. 3 shows the components of ICT emissions, including personal user devices, networks, and data centers [5]. Notably, pervasive and mobile computing (PMC) technologies, including distributed systems and mobile networks, are major contributors within these categories. As shown in Fig. 4, mobile and embedded devices account for a substantial portion of the embodied GHG emissions for user devices, with smartphones and laptop PCs among the most significant contributors. Similarly, Table 1 presents network GHG emissions, indicating that mobile networks are responsible for the majority of both embodied and use-stage emissions among network types. These insights emphasize the substantial role of pervasive and mobile computing in driving ICT-related emissions, underscoring the need for targeted strategies to manage and mitigate these environmental impacts. Further driving the increase in energy within the ICT sector are large AI models, particularly those running in extensive data center facilities. These models can require up to 3 to 5 million gallons of water daily for cooling, adding substantial pressure on energy and water resources and intensifying ICT's environmental footprint. "The shift towards AI has dramatically increased energy consumption in data centers, with the International Energy Agency (IEA) predicting a doubling of global data center electricity demand between 2022 and 2026, driven significantly by AI's energy-intensive model training processes" [6].

Advancements in computation techniques are also required, given that climate-related tasks rely heavily on computationally intensive simulations and vast amounts of data from Earth observations. Table 2 shows illustrative climate-smart computing research challenges and opportunities within various computing subareas identified by the U.S. National Science Foundation [1]. The components of climate-smart computing include:

> "(1) smart sensor-based networks or self-adaptive robots for real-time data collection under extreme conditions, (2) disaster-resilient communication networks, (3) advanced computing infrastructures for efficient data storage and aggregation, and high-speed, heterogeneous computing resources for processing vast volumes of climate-related data and complex climate models, (4) state-of-the-art data-driven computational modeling and high-precision simulations for deeper insights and discoveries, (5) innovative climate informatics, including AI, for enhanced analysis and prediction, and (6) human-centered computing approaches for visualizing key challenges, impacts, and solutions."

In this paper, we adopt NSF's use of the term *informatics* to refer to "the study and development of computational techniques for managing and utilizing information throughout its entire lifecycle" [7], encompassing activities such as application domain & data understanding, data preparation, modeling & analysis, evaluation, and deployment [8].

***Key insights.*** Our aim here is to provide a visionary introduction to open problems in climate-smart computing. We explore the challenges and opportunities associated with both the current application of computing and the advancement of computing techniques in the realms of climate understanding, resilience, mitigation, and adaptation. The key insights of the paper are summarized as follows:

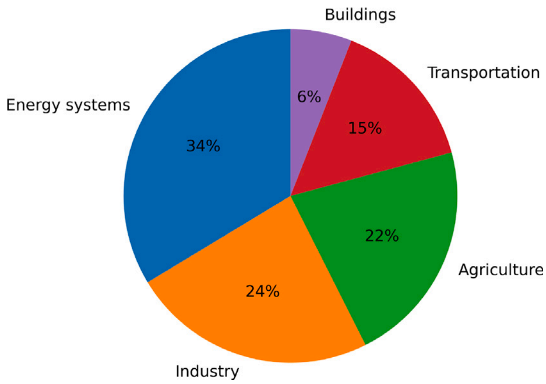



**Fig. 2.** Total global greenhouse gas emissions by economic sector in 2019 [2].

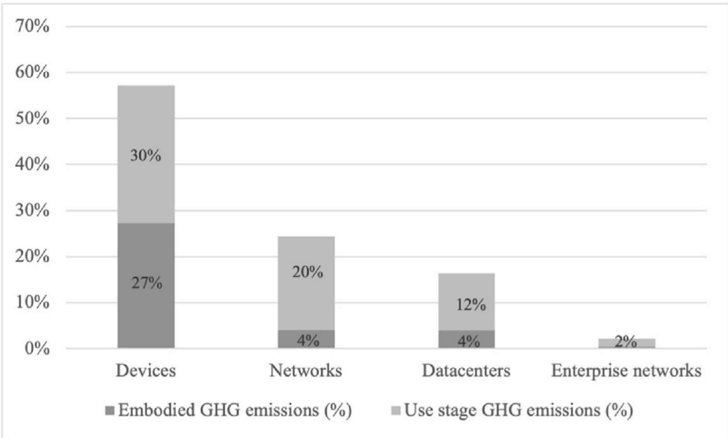



**Fig. 3.** Total ICT sector carbon footprint (2020) [5].

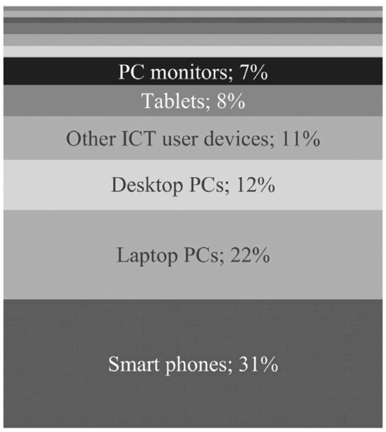



**Fig. 4.** Allocation of embodied GHG emissions for devices. Numbers included only for the most contributing device types [5].

- Computing is central to addressing climate change, with applications supporting climate understanding, resilience, mitigation, and adaptation through data-driven approaches and advanced modeling.
- PMC technologies play an essential role in building climate resilience by supporting early warning systems and real-time monitoring. IoT-enabled alerts and mobile networks enable communities to prepare for and respond to extreme climate events like floods, wildfires, and storms, enhancing adaptive capabilities at the local level.

**Table 1**
Network GHG emissions for 2020 allocated to network types [5].

| | Use stage GHG (Mtonne $CO_2$e) | Embodied GHG (Mtonne $CO_2$e) | Total GHG (Mtonne $CO_2$e) |
|---|---|---|---|
| Total networks | 153 | 31 | 184 |
| Mobile networks | 101 | 17 | 118 |
| Fixed broadband | 38 | 14 | 51 |
| Fixed telephony | 14 | 0 | 14 |

**Table 2**
Representative research topics for climate-smart computing [1].

| Computing subareas | Climate-related challenges and opportunities |
|---|---|
| Sensors, clocks, IoT, devices, edge computing, etc. | Real-time data collection under extreme conditions |
| Networks (wireless, wired) | Resilient to natural disasters |
| Infrastructure (e.g., Cloud, clusters, etc.) | Efficient data storage and aggregation |
| Simulation, Digital Twins | Deeper understanding and new discoveries of climate |
| Informatics (e.g., AI, Data Science) | Provide advanced analysis and prediction capabilities |
| Human-centered computing | Understanding and visualizing key challenges and impacts |

- Effective integration of diverse climate data sources, including IoT and satellite data, enables real-time climate modeling and enhances forecasting accuracy for timely responses to climate events.
- As computing demand grows, PMC technologies, including mobile networks and IoT devices, are contributing substantially to emissions by the ICT sector due to their extensive deployment and power requirements. Reducing PMC's environmental footprint through low-power computing, energy-efficient hardware, and sustainable data management practices is essential.
- Interdisciplinary collaboration ensures that climate-smart computing aligns with scientific and societal needs, while ethical and responsible practices prioritize equity, data privacy, and environmental justice in climate solutions.

***Scope.*** Our recommendations cover open research problems related to climate change, opportunities we see to apply computation science to these problems and examples of areas where we believe advancements in computing techniques are needed. While some examples and data are drawn from the U.S. due to the high availability and accessibility of relevant data, our larger aim is to address global climate challenges, and many figures reflect broader trends where possible. The paper is not an exhaustive summary from either a climate or computing perspective. Interested readers can refer to Intergovernmental Panel on Climate Change (IPCC) reports (e.g., [2,9]) or other materials, such as the book *Mathematics and Climate* [10], *Insolvent: How to Reorient Computing for Just Sustainability* [11], the environmental awareness section in the *Red Blue Dictionary* [12] and the Special Issue on Computing and Climate in the Computing in Science & Engineering journal [13], among others.

***Outline.*** The remainder of this paper is structured as follows:

- Section 2, Illustrative Patterns in Climate Change, provides essential background on climate trends, impacts, and extreme events. This section sets the stage by describing how climate change drives computational needs, from modeling global climate systems to tracking local weather anomalies.
- Section 3, Climate Applications of Computing, showcases how computing supports climate understanding, resilience, mitigation, and adaptation. Examples include advanced simulations for climate projections, predictive analytics for extreme events, and tools for managing energy-efficient infrastructure. This section also introduces the contribution of PMC in climate applications through technologies such as nanosatellites and IoT devices, which enable real-time data collection and localized adaptation.
- Section 4, Emerging Challenges in Climate-smart Computing, outlines specific computing advancements required to support climate goals. Here, we discuss how computing must evolve, focusing on topics like decarbonizing computing, building climate-resilient systems, and enhancing interdisciplinary collaboration. Further, we discuss the trade-offs between the pros and cons of additional computing in the context of climate change, given computing itself also produces emissions. This section also discusses challenges in integrating large, diverse climate datasets and ensuring responsible, human-centered computing practices.
- Section 5, Conclusions and Future Work, summarizes key insights and takeaways and calls for sustained research and education efforts. This final section emphasizes the role of the computing community in addressing urgent climate challenges.
- An Appendix provides a table of acronyms (Table A.6) and a glossary of key terms (Table A.7)

## 2. Illustrative patterns in climate change

To keep the article self-contained, we summarize key climate change patterns from recent centuries, providing essential background for the computing community. Additionally, we provide formal definitions of the four key areas of climate-related action – Understanding, Resilience, Mitigation, and Adaptation – as these serve as the main themes tying the paper together.

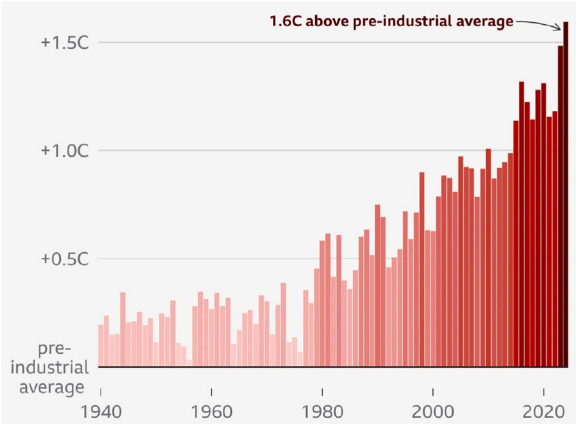



**Fig. 5.** The trend of global average surface temperature [14].

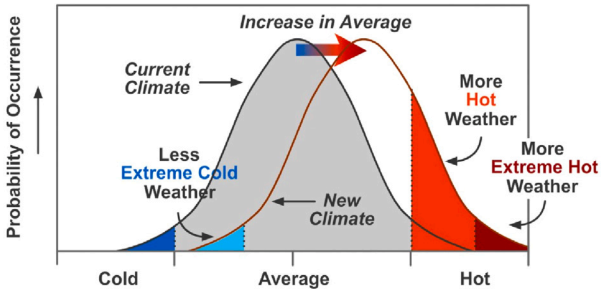



**Fig. 6.** A conceptual representation of the shift in the probability distribution for average and extreme temperatures as a result of global warming [15].

Increases in human activities such as industrialization, increased consumption of natural resources, deforestation, and fossil fuel burning result in high GHG emissions (as shown in Fig. 1). For instance, industrial processes release significant amounts of carbon dioxide ($CO_2$) and methane ($CH_4$), both potent greenhouse gases. The transportation sector, with its reliance on fossil fuels, is another major contributor. These activities not only increase GHG levels but also reduce the Earth's ability to absorb these gases through natural sinks like forests and oceans, exacerbating the problem.

As shown in Fig. 5, there is a warming trend in the last century that cannot be explained by long-term or short-term natural variations and events [14,16,17]. According to the latest Synthesis Report from the IPCC [18], "it is likely that well-mixed greenhouse gases (GHGs) contributed to a warming of 1.0 °C to 2.0 °C". This significant increase in global temperatures has profound effects on the climate system. Additionally, the variability of precipitation is increasing in a warmer climate [19], indicating more erratic and extreme weather patterns. Rising temperatures cause plant and animal species to migrate to higher altitudes and away from the equator, seeking cooler habitats. This shift disrupts ecosystems and biodiversity. It also alters the timing of seasons, causing spring to arrive earlier and autumn to come later, which can affect traditional agricultural cycles and natural ecosystems.

That rise in temperature explains the increased frequency and intensity of climate extremes (e.g., heatwaves, flooding) supported by statistics and physical science. Fig. 6 illustrates a statistical view using a conceptual representation of the temperature distribution shift. It can be observed that the frequency of extremely high temperatures increases non-linearly, with "a small increase in average temperatures leading to large changes in the frequency of extreme heat events" [15]. Critically, more heat events emerge at the upper tail (far right in Fig. 6), which would not have occurred under normal climate conditions. From a physical science perspective, it is known that warmer air holds more water vapor. This means that rising temperatures lead to heavier rainfall and increased flood risks. Rising temperatures also accelerate the melting of glaciers and polar ice, contributing to sea level rise and coastal erosion. Other trends are summarized in Table 3 [20].

To avert the worst impacts of climate change, the Intergovernmental Panel on Climate Change (IPCC) [2,9] has defined four key areas of climate-related action:

- **Understanding**: Comprehending the drivers of planetary processes and projecting how these processes might change under various scenarios, such as increased greenhouse gas emissions [21].
- **Resilience**: The ability of our social, ecological, or socioecological systems and its components to anticipate, reduce, accommodate, or recover from the effects of a hazardous event or trend in a timely and efficient manner [9].
- **Mitigation**: The human interventions to reduce the source of greenhouse gas emissions and protect natural carbon sinks [2].

**Table 3**
Trends in climate and weather extremes in a warmer world [20].

| Extreme event | Trends |
|---|---|
| Heavy Precipitation | Increasing instances of heavy and intense rainfall and snowfall, leading to a higher risk of flooding. |
| Storms | More frequent and stronger storms such as hurricanes due to the increased energy in a warmer atmosphere. |
| Atmospheric Rivers | Longer, wider, and wetter atmospheric rivers, resulting in greater flood damage. |
| Heatwaves | More frequent, hotter, and longer-lasting heatwaves. |
| Drought | Increased likelihood of droughts, with warmer temperatures causing drier and longer drought periods. |
| Wildfires | Larger and more dangerous wildfires occur over longer seasons and in more unexpected areas. |

- **Adaptation**: The singular of adjustment in natural or human systems in response to actual or expected gradual climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities [9].

These four areas are intricately connected. Techniques for climate understanding, such as global climate system modeling [21], provide foundational knowledge to comprehend planetary processes and predict future climate scenarios. Based on this foundational understanding, other climate change actions are developed in an interdependent manner. For example, climate-resilient development that integrates adaptation measures with mitigation strategies promotes sustainable development universally [9]. In the rest of this paper, we describe how specific computing techniques can help with each area, highlighting their pivotal roles.

## 3. Climate applications of computing

Computing is a crucial tool in climate action. In this section, we discuss societal applications of computing techniques across climate understanding, resilience, mitigation, and adaptation. Within each subsection, subheadings connect the paragraphs with the computing components from Table 2, so readers can easily spot the categories of computational work involved.

### 3.1. Climate understanding

Computational techniques provide valuable insights into the complex processes driving climate change, from monitoring climate change to modeling and assimilating observational data. By leveraging these techniques, researchers can better inform policymakers and the public about the impacts of climate change and guide efforts to mitigate and adapt to these changes. Computing areas crucial for understanding climate change include simulation, data assimilation, computing infrastructure, sensors, and informatics. Each area plays a vital role in advancing our knowledge of climate processes and improving climate models.

***Simulation.*** Analyzing and projecting the amount of carbon dioxide and other greenhouse gases emitted in coming decades can help understand and project the trend of global temperatures under different scenarios. Example simulation models include global climate models (GCMs) [22]. These models use many different factors such as water vapor, carbon dioxide, heat, and the Earth's rotation as inputs to compute the interaction between these factors with the ocean, air, and land, and then produce a projection of how the Earth's climate may change. An example is shown in Fig. 7 [23]. The two subfigures show annual historical and a range of plausible future carbon emissions in units of gigatons of carbon (GtC) per year (left) and the historical observed and future temperature change that would result in a range of future scenarios relative to the 1901–1960 average, based on the central estimate (lines) and a range (shaded areas, two standard deviations) as simulated by global climate models (right). For example, by 2081–2100, the projected range in global mean temperature change is 1.1°–4.3 °F under the lower scenario (RCP2.6; 0.6°–2.4 °C, green) and 5.0°–10.2 °F under the higher scenario (RCP8.5; 2.8°–5.7 °C, orange). In addition to these applications, computational simulation techniques are essential for developing and running complex polar climate system numerical models. For example, regional climate models and ice sheet models are used to simulate the response of the polar regions to different climate-forcing scenarios.

***Infrastructure.*** Advanced computing infrastructures, including high-performance computing (HPC), cloud computing, GPUs, and data centers, are pivotal in climate simulation as well as processing, analyzing, and storing vast amounts of climate data from various sources like satellite observations, in-situ measurements, and climate simulations. HPC systems are essential for running complex climate models requiring significant computational power, enabling high-resolution simulations to capture fine-scale climate processes crucial for understanding regional climate impacts and extreme weather events [24]. Notable examples include the NCAR supercomputers, such as Cheyenne [25] and the upcoming Derecho [26], which provide substantial computational resources for climate modeling and simulation. Similarly, Japan's Earth Simulator has been a cornerstone in climate research, offering advanced capabilities for simulating climate systems with high precision [27].

Cloud computing platforms like Amazon Web Services (AWS) and Microsoft Azure provide scalable and flexible resources for storing and processing large climate datasets, such as AWS Earth [28], Google Earth Engine [29], etc. These platforms offer tools for distributed computing, data analytics, and machine learning, facilitating collaborative research and real-time data analysis [30]. GPUs also play a significant role in accelerating climate model computations, enhancing the efficiency and speed of data processing tasks.

Data centers are critical for managing climate data, with innovative use of renewable energy sources and advanced cooling techniques, significantly reducing the carbon footprint of data storage and processing [31,32]. Efficient data management and storage solutions, like data lakes and distributed databases, enable centralized storage of heterogeneous climate data, supporting data sharing and collaboration among researchers worldwide.

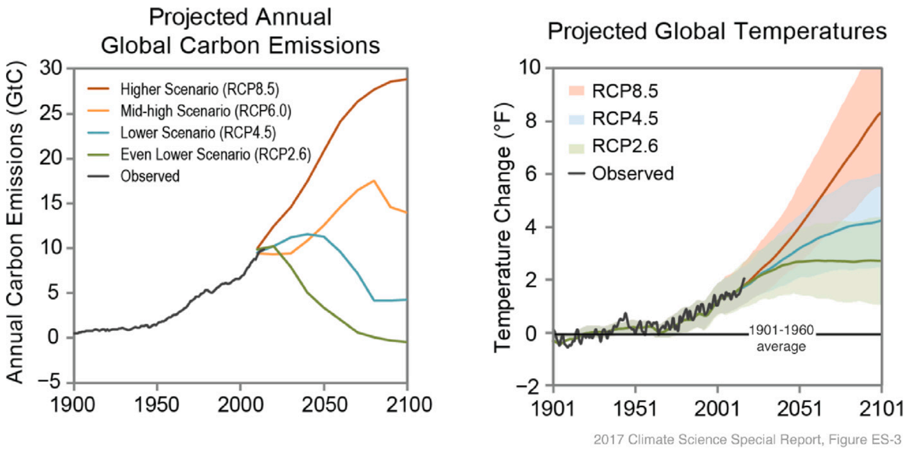



**Fig. 7.** The annual historical and a range of plausible future carbon emissions (left) and the historical observed and future temperature change that would result for a range of future scenarios (right) [23].

***Sensors.*** Climate change projections are reliant on the use of sensors in climate data collection to provide critical information (e.g., initial and boundary conditions) for understanding and modeling climate change. Various types of sensors are deployed to monitor different environmental parameters. Satellite-based sensors, such as those used in Earth Observation (EO) programs like the Sentinel and Landsat missions, measure sea surface temperatures, sea ice extent, and atmospheric moisture with high spatiotemporal resolution. These sensors capture data on the Earth's biological, physical, and chemical processes using remote sensing technologies, including multispectral and hyperspectral imaging, radar, and LiDAR [33,34]. Ground-based sensors, including automatic weather stations, capture data on temperature, humidity, wind speed, and precipitation. Oceanographic sensors deployed on buoys and moorings measure sea temperature, salinity, and currents, contributing to a better understanding of ocean dynamics [35]. Additionally, ice-tethered profilers collect data on ice thickness and subsurface temperature, which are vital for studying ice sheet dynamics and permafrost conditions [33]. These sensors, combined with computing techniques, enable the continuous monitoring of climate variables, enhancing the accuracy of climate models and the reliability of climate predictions.

Another important application of sensing techniques is the study of ice sheet dynamics. Ice sheets, such as the Greenland and Antarctic ice sheets, are massive reservoirs of freshwater that can significantly contribute to sea-level rise if they melt. Remote sensing methods like interferometric synthetic aperture radar (InSAR) and altimetry data processing enable researchers to monitor ice sheet surface elevation changes, ice flow velocities, and ice mass balance. These techniques help identify regions of accelerated ice loss and improve our understanding of the mechanisms driving ice sheet instability [36,37].

***Informatics.*** Computing techniques are crucial for analyzing and interpreting the vast amounts of data collected from climate observing systems, such as automatic weather stations, oceanographic moorings, and ice-tethered profilers. Data assimilation techniques, such as Kalman filtering and variational methods, combine observations with model predictions to improve the accuracy and reliability of climate simulations [36,37]. However, missing data [38–40] poses significant challenges in climate data science. Gaps in data can lead to biases and uncertainties in climate models and hinder the validation of model outputs. Advanced imputation techniques and robust data assimilation methods are essential to address these issues and ensure the integrity of climate research [38,41].

Permafrost, or permanently frozen ground, is another critical component of the climate system. Machine learning algorithms applied to remote sensing data can help map permafrost distribution and monitor its thermal state. This is important for understanding the potential release of greenhouse gases, such as methane and carbon dioxide, from thawing permafrost, which can further amplify global warming [42]. The combination of observational data with model simulations [43–46] can significantly enhance the ability to capture and predict spatial variability in climate phenomena.

Another primary application of informatics in computing is the study of sea ice dynamics. Satellite remote sensing data and computing techniques enable researchers to monitor changes in sea ice extent, thickness, and motion. For example, machine learning algorithms can be applied to satellite imagery to automatically detect and track sea ice features, such as leads (linear cracks in the ice), polynyas (areas of open water surrounded by sea ice), and ice floes (large pieces of floating ice). These techniques help quantify the rate of sea ice loss and improve our understanding of the underlying processes driving these changes [36,42,47–49]. Additionally, the combination of satellite data with in-situ measurements allows for the validation and enhancement of model accuracy, providing a more comprehensive understanding of spatial variability in sea ice dynamics [37,50].

### 3.2. Climate resilience

Climate extremes caused by climate change, such as heatwaves, droughts, and megastorms, can result in economic losses, injuries, and even fatalities [53], as shown in Fig. 8 [51]. For example, extreme heat can cause heat stroke and dehydration, leading to death.


**Fig. 8.** Climate change can affect climate extremes and result in major impacts on society [51].

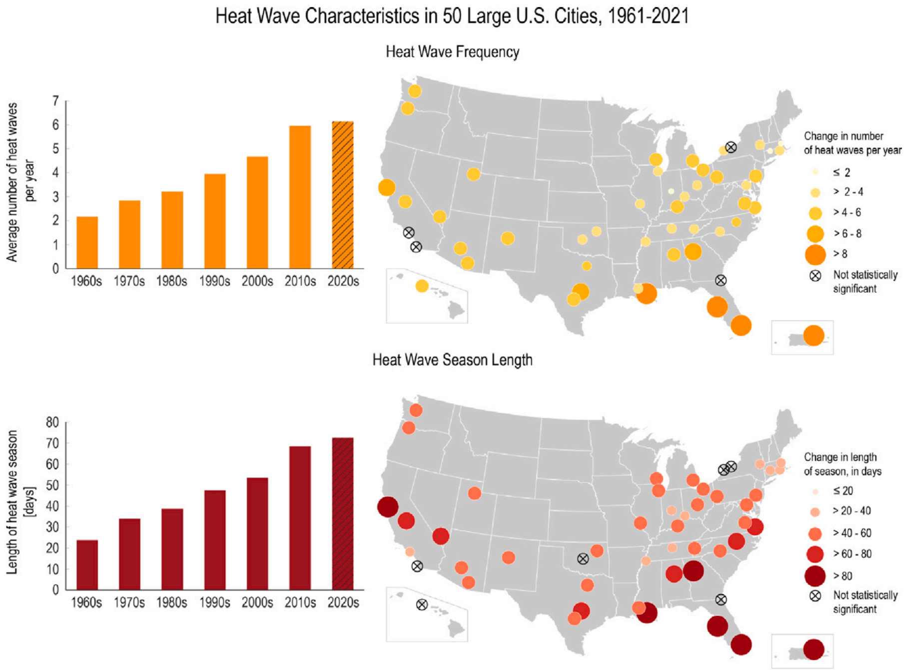
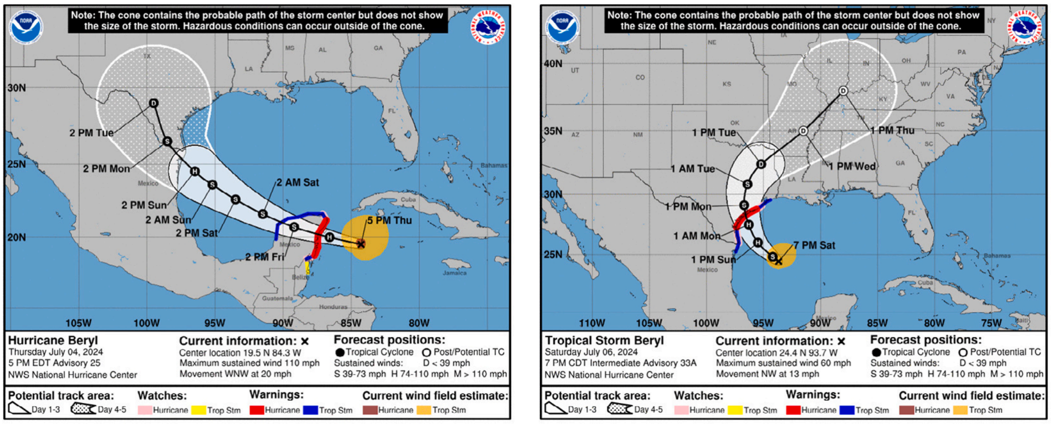



**Fig. 9.** Upper: The number of heat waves per year (frequency); lower: The number of days between the first and last heat wave of the year (season length) [52].

Between 14 and 19 June 2024, "at least 1,301 people on the Hajj pilgrimage to Mecca died due to extreme heat, with temperatures exceeding 50 °C (122 °F), making it the deadliest Hajj to date" [54]. Increased global temperatures exacerbate these hazards, making them more extreme and frequent. Fig. 9 illustrates the increase of heatwaves in the U.S., with bar graphs and maps showing changes in the number of heatwaves per year (frequency) and the number of days between the first and last heatwave of the year (season length) across all 50 metropolitan areas by decade [52]. The size/color of each circle in the maps indicates the rate of change per decade. It is clear that heatwaves are becoming more frequent and intense with global warming. Therefore, the ability to anticipate, prepare for, and respond to these extremes—collectively known as climate resilience—is crucial to reducing the impact of climate change. Table 4 provides a summary of example computing techniques to help reduce the risks associated with climate extremes. Here, risk is defined with the multiplicity of two components: the probability of extreme events and the exposure to these

**Table 4**
Computing techniques can help with different stages in climate resilience.

| Stage | Computing techniques |
|---|---|
| Risk assessment | *Sensors*: Risk maps |
| Planning | *Simulation*: Scenario-based resilience planning |
| Response | *Cross-cutting*: Geo-targeted alert warning with trust building |
| Recovery | *Cross-cutting*: Resource allocation optimization and infrastructure rebuilding simulations |
| Risk mitigation | *Informatics*: Database of best practices and recommendations |




(a) Thursday July 04, 2024 (b) Saturday July 06, 2024

**Fig. 10.** An example tropical storm track forecast cone over two days of observation and prediction [59].

events. The following illustrates some of the ways to contribute to climate resilience, such as sensors, simulation, informatics, and human-centered computing.

***Sensors.*** At the risk assessment stage, a primary application of sensor techniques is in anticipating extreme events and providing early detection to generate risk maps. For instance, the frequency and intensity of wildfires have dramatically increased over the past decade, leading to extensive damage to both ecosystems and human settlements [55]. While complete prevention of wildfires is not feasible, their early detection and precise geolocation at initial stages can significantly mitigate the resulting destruction. Traditional detection methods often depend on witness reports. As a result, incipient fires, especially in the wilderness, may remain undetected for extended periods, producing only limited visible indicators such as small smoke plumes or subtle changes in temperature and gases. Sensing techniques are necessary for more efficient and accurate monitoring of vast and remote areas. For example, ground-based sensors can detect conditions conducive to wildfires, such as hot, dry weather, and strong winds. Chemical sensors can also provide real-time data on carbon dioxide and smoke particles [56,57]. Unmanned aerial vehicles (UAVs) equipped with these sensors have the potential to offer high spatial and temporal resolution data, facilitating the mapping of chemical fire signatures in complex terrains before they are visibly detectable [58].

***Simulation.*** Scenario-based resilience planning is a vital strategy for decision-makers planning for extreme events. This process involves considering various potential manifestations of high-risk extreme events and exploring the effects of multiple potential future conditions on important resources. During this process, computing techniques are utilized to develop prediction models that estimate future conditions, aiding in the identification and selection of action plans [60]. A final step involves using computing systems to optimize actions if a given scenario occurs. For instance, evacuation planning, a common strategy to protect people from the impacts of extreme events such as wildfires and hurricanes, relies heavily on computing-based models for both planning and managing evacuation during disaster response phases [61,62].

***Informatics & human-centered computing***. During heat waves or other extreme events, humans need clear and actionable information about how to protect themselves. Informatic techniques can be used to develop databases of information (e.g., public buildings with AC that can serve as cooling centers) or best practices (e.g., recommendations by body size for water intake). Human-centered computing can disseminate this information to the public, including sending warnings, assigning shelters, and presenting schedules through trusted channels (e.g., priests, etc.).

During rapidly moving events such as hurricanes, communicating with the public requires special consideration of spatiotemporal variances. Fig. 10 shows the track forecast of the center of Hurricane Beryl in July 2024 [59]. The current and predicted positions of the center of the storm are denoted by 'X' and black dots, respectively. The cones represent the probable tracks of the center

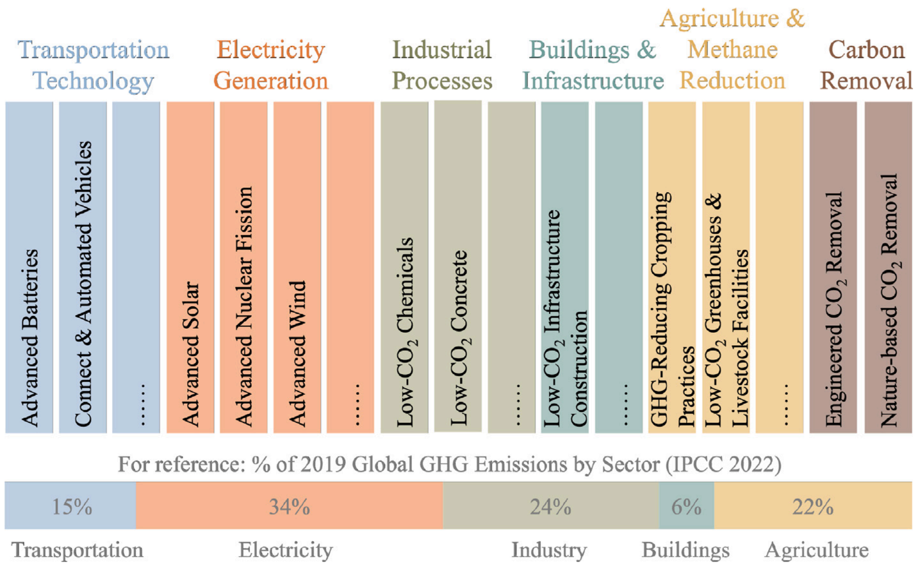



**Fig. 11.** Sectoral innovations for global net-zero game changers [2,63].

of the tropical storm, and the level of warning for nearby coastal areas is indicated by color. The shifts in the predicted trajectory and intensity of the hurricane reflect the spatiotemporal variation and data complexity inherent in these predictions. Conveying the uncertainty of these predictions in public service announcements is very challenging. There is a need to assess the existing gaps in public understanding and develop new techniques to effectively communicate these uncertainties, ensuring that the information is both accessible and actionable. Without such efforts, public distrust of weather advisories may put lives in danger.

### 3.3. Climate change mitigation

Climate change mitigation includes measures to slow the release of GHG into the atmosphere, either by reducing the source (e.g., decarbonization of transportation and other industries) or by enhancing the sinks that remove these gases from the atmosphere (e.g., ocean and forest preservation). Numerous efforts have been made to identify opportunities for climate change mitigation. Fig. 11 candidate sectoral innovations of net-zero "game changers" [63]. The bottom part of the figure presents the global GHG emissions by sector as of 2019 [2], providing a context for where emissions reductions are most urgently needed. The top portion of the figure offers an overview of technological innovations targeting GHG reduction across different economic sectors. These innovations are organized by sector, including transportation technology (e.g., advanced batteries, connected and automated vehicles), electricity generation (e.g., advanced solar, nuclear fission, wind), industrial processes (e.g., low-$CO_2$ chemicals, low-$CO_2$ concrete), buildings and infrastructure, agriculture and methane reduction, and carbon removal. Each category highlights specific advancements within the sector to drive emissions reduction. This section further discusses the role of computing components in supporting and accelerating these innovations.

***Sensors & networks.*** In the field of urban planning, pervasive computing supports smart building infrastructure equipped with real-time data collection and analysis capabilities. These buildings utilize IoT devices, including smart thermostats, lighting systems, and energy management systems, which can dynamically adjust settings of heating, ventilation, and air conditioning (HVAC) systems [64] based on occupancy patterns, external weather conditions, and energy usage trends [65]. Additionally, integrating renewable energy sources with smart grid technology allows buildings to optimize energy use by balancing supply and demand, storing excess energy, and reducing reliance on non-renewable sources [66].

***Optimization algorithms.*** An impactful application of computing for climate change mitigation is carbon-aware site selection [67], that is the strategic selection of facility locations to minimize the associated carbon emissions. Carbon-aware site selection is particularly important within the supply chain industry. Each site – including suppliers, manufacturing plants, distribution centers, and customer locations – serves as a distinct element in the local transportation ecosystem. This ecosystem is characterized by infrastructure, transport modes, reliability, and cost considerations. By selecting site locations that minimize transportation distances between them, companies can significantly reduce greenhouse gas (GHG) emissions associated with product distribution. These techniques become increasingly effective as the volume of materials to be transported grows.

***Informatics.*** Computing techniques play a big role in reducing GHG emissions in transportation. One way is by improving understanding and modeling of tailpipe emissions, the biggest source of emissions in the transportation sector. The engine control units of modern conventional vehicles are computers that make the engine run with a particular objective including maximizing

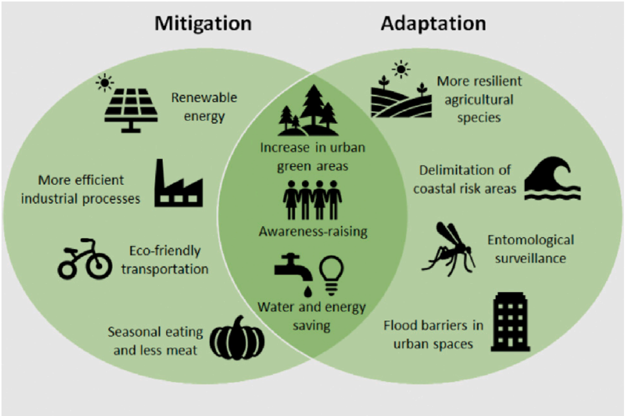



**Fig. 12.** Examples of climate mitigation and adaptation [75].

power output, maximizing fuel economy, and minimizing tailpipe emissions. The simplest algorithm is a widely used look-up table of control variables, like fuel delivery and ignition timing, that is filled using extensive pre-production testing. With the advent of promising machine learning techniques, researchers have investigated the performance of physics-aware machine learning models in modeling emissions like NOx [68] and soot [69] using appropriate engine variables. These models help better understand the emissions phenomenon by modeling the non-linear dynamics of engine combustion that lead to anomalous amounts of GHG emissions. In addition, software tools [70,71] have been developed that evaluate the electrification potential of different types of vehicle fleets. Another work [67] highlights the potential mitigating impacts of a vehicle-to-grid infrastructure (V2G), a bi-directional charging system that enables EVs to both absorb excess power as well as push energy back to the grid. Intelligent siting of charging infrastructure can help encourage broader adoption of electric vehicles while focusing on locations with low carbon intensity and renewable energy sources. Finally, smart charge scheduling can be used to help balance energy grid demand and the financial and environmental costs of charging electric vehicles [72].

In addition to electrification, intelligent energy management is also a key to speeding this transition and minimizing emissions. Eco-routing involves optimizing routes for transportation networks to minimize fuel consumption and greenhouse gas emissions. By using real-time traffic data, AI algorithms can determine the most efficient routes, reducing overall travel time and environmental impact.

***Simulation.*** Several simulation tools and digital twins also help in mitigating GHG emissions in the transportation sector. SUMO (Simulation of Urban MObility) [73] is widely used to model and predict traffic flows, to help optimize urban planning and reduce vehicular emissions. By simulating various traffic scenarios, SUMO helps develop more efficient transportation networks, consequently mitigating the carbon footprint of urban mobility. A similar simulation tool, FASTSim (Future Automotive Systems Technology Simulator) [74], has been instrumental in evaluating the efficiency and emissions of different vehicle technologies, including electric and hybrid vehicles. The tool allows researchers to simulate the performance of these vehicles for pre-defined trips and under various conditions, providing valuable insights into their potential for reducing GHG emissions. Such traffic simulators and digital twins play a crucial role in helping policymakers, fleet managers, and vehicle manufacturers formulate strategies that can help mitigate the ill effects of vehicular emissions.

### *3.4. Climate change adaptation*

Adaptation to climate change refers to the process of adjusting systems in response to actual or expected gradual climatic stimuli or their effects. This strategy is essential for reducing vulnerability across sectors such as agriculture, infrastructure, water resources, and human health. Some illustrative examples that differentiate adaptation from mitigation are shown in Fig. 12 [75]. For example, anything that aims to reduce carbon dioxide emissions is mitigation, such as renewable energy and eco-friendly transportation. Increasing urban green areas can both mitigate and promote adaptation to climate change while adapting agriculture based on entomological surveillance is an example of adaptation. Both mitigation and adaptation actions are crucial for averting the worst impacts of climate change. Mitigation will limit the future impacts of climate change, and adaptation will help the world cope with those changes. However, trade-offs involving factors such as vulnerability, economic development, and fair share climate contributions may tip the scale in one direction for a community. For example, a smaller nation like Tuvalu will focus primarily on adaptation, as “it is a low-lying island nation that faces the near-term threat of sea level rise” [75]. Effective adaptation safeguards against the adverse effects of climate change, ensuring the continued functioning and resilience of societies and ecosystems. In this context, climate-smart computing plays a pivotal role in enhancing adaptive capacity. Through real-time monitoring, data analytics, and machine learning, smart computing can significantly improve the effectiveness and efficiency of adaptation strategies.

Besides understanding how adaptation relates to mitigation, some readers may be interested in how adaptation relates to resilience. In this context, it is useful to categorize climate impacts as either extreme events or gradual changes. Extreme events,

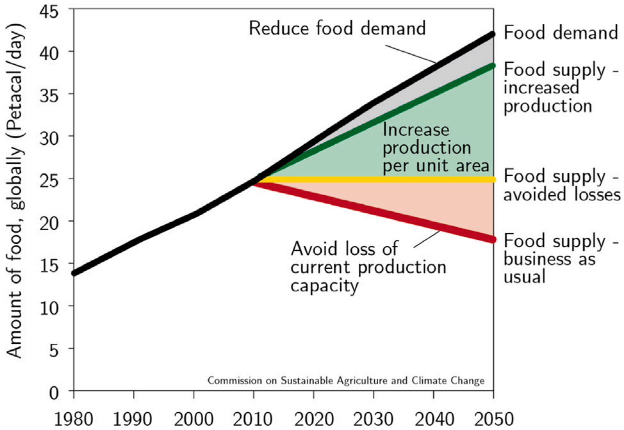



**Fig. 13.** Adaptation to balance food supply and demand [76].

including extreme heat, wildfires, and droughts, were discussed in Section 3.2 and illustrated in the bottom two rows of Fig. 8. Gradual changes include sea level rise, melting of glaciers and ice sheets, permafrost thawing, the gradual movement of plant and animal species to higher elevations and away from the equator, as well as the gradual loss of productivity of agriculture and forests under a business-as-usual scenario. While these events may not risk the immediate loss of life and livelihoods, and mitigation can take time, these gradual changes risk major losses over centuries if not decades. Thus, it is important to plan actions for adaptation to such gradual changes. An example of balancing food supply and demand is shown in Fig. 13 [76]. Food demand will grow in the future due to population growth and changing diets (black line), and the food supply must meet this demand. However, under a business-as-usual approach, food production will decrease over time due to climate change (red line). To ensure the world remains resilient against hunger, the large resulting gap between food supply and demand should be bridged by adaptation approaches (yellow and green lines). The following discusses how different components of computing are crucial for adaptation.

***Sensors.*** Sensors play a pivotal role in climate adaptation, from agriculture to urban planning. Smart sensors in buildings can contribute to energy efficiency by detecting occupancy and adjusting lighting and air conditioning accordingly [77,78]. In agriculture, sensing is important for entomological surveillance. Tracking the movements and population of insects can help detect the presence of pests that affect crop health [79,80]. This allows farmers to implement timely interventions, reducing crop damage and improving yield. In addition, water resource management benefits from sensors that monitor soil moisture, rainfall, and potential water leaks to help optimize irrigation systems and conserve water [81]. Based on these applications, precision agriculture uses technologies such as sensors, GPS, and data analytics to collect and analyze detailed information about crop conditions, soil health, and environmental factors. Precision agriculture recognizes that soil is a spatially variable continuum and that its impacts on food production are also spatially variable [82]. This continues to be the building block on which site-specific crop management and precision pasture management have developed. By acknowledging and leveraging this spatial variability, precision agriculture helps optimize field-level management of crop farming practices, leading to more efficient use of resources and increased agricultural productivity.

***Simulation.*** Using projected climate data and elevation maps, simulations can model sea-level rise and its effects on coastal regions [83–85]. This can help planners identify vulnerable areas and develop appropriate protective measures, such as flood barriers or evacuation routes. Similarly, flood simulations can predict inland areas prone to flooding, helping communities prepare and respond effectively [86,87].

Aside from disaster management, urban planning can also benefit from simulations that predict the cooling effect of green infrastructure to reduce urban heat islands [88]. In agriculture, simulation models can predict the impacts of climate variables on crop yield, guiding farmers in selecting optimal planting times and crop varieties [89,90].

***Informatics.*** Water resource management is crucial in adapting to changing precipitation patterns and droughts. Predictive models forecasting water demand and availability aid in efficient water resource allocation, and smart irrigation systems can use sensors and AI to optimize water usage in agriculture to conserve water [91]. For example, autonomous agents such as aerial drones can be used to monitor crop health and apply resources efficiently [92,93]. In addition, informatics can help develop drought-resistant crops and adjust planting schedules by analyzing soil health, weather patterns, and crop performance data. For example, bioinformatics analysis of genetic data from different agricultural species can identify traits that confer resistance to climate stressors [94].

Many populous areas will also need to adapt to an increase in the level and frequency of uncomfortable heat. Addressing urban heat islands by developing green roofs, urban forests, and reflective surfaces helps to cool cities and reduce air conditioning needs [95]. Geographic Information Systems and remote sensing can help map urban heat islands and identify optimal locations for such green infrastructure [96].

**Table 5**
Computing Assumptions Violated by Climate Change (e.g., Global Warming and Impacts).

| Assumptions violated | Possible approaches |
|---|---|
| Economics is the main objective, not environmental impact | Decarbonizing computing |
| More computing is always better | Study the tradeoffs between the pros and cons of additional computing |
| Black swan events exceeding current design specifications are rare | Climate resilient computing |
| Current computing techniques are adequate for addressing the volume, velocity, and variety of climate data | Climate-scale computing techniques |
| Isolated paradigms (e.g., physics, computing) can adequately address climate-related issues | Interdisciplinary convergence |
| Solution quality is the sole metric of model evaluation | Responsible computing |

### *3.5. Climate debate*

There is an ongoing debate surrounding climate change, as highlighted in the red-blue dictionary entries under environmental awareness [12]. For example, when discussing sustainability, one side emphasizes resource renewal and minimal ecological harm—arguing that reliance on fossil fuels is unsustainable due to finite resources and environmental damage. They often propose renewable energy sources such as solar and wind, and criticize large-scale farming methods for harming ecosystems and public health. In contrast, the other side stresses the economic and employment implications of phasing out fossil fuels, points to the cost and reliability challenges of renewables, and defends industrial farming for its efficiency and affordability. Diving into the key areas of climate-related action introduced in this section, both sides share a common interest in resilience and economics. However, one perspective emphasizes mitigation measures to achieve net-zero emissions (e.g., the Paris Agreement), while the other prioritizes adaptation strategies from a consumer and market-oriented viewpoint. Nonetheless, as illustrated in Fig. 12, there are potential win-win solutions – such as water and energy conservation and increased urban green spaces – that could address climate challenges in ways that benefit multiple stakeholders.

## 4. Advancing climate-smart computing

While computing techniques can be successfully applied to many climate-related tasks, the process of climate change itself often undermines traditional computational assumptions, posing significant challenges to existing methods. For instance, traditional informatics techniques rely on the notion that past conditions can predict future events. However, this assumption may be violated in climate-related tasks. Factors such as the non-stationarity induced by climate change, the rarity of specific climate events, the high costs associated with ground truth collection, and the necessity to adhere to natural laws like the conservation of mass, can overwhelm traditional data-driven machine learning models.

Consequently, there is a critical need for advancements in computational techniques to address these emerging challenges. For example, purely data-driven analytic models typically require large training datasets and often struggle to produce results consistent with physical laws. There is a pressing need for research into the systematic integration of physical science principles, such as mechanistic process-based models, into machine learning frameworks [97]. Another example is the need to shift from an economic focus to a climate and environment-centric approach in computational design. Sensors and devices previously optimized primarily for economic efficiency now need to also consider environmental impacts. Potential approaches could include recycling-friendly designs using sustainable materials and multi-objective optimization that balances economic and environmental impacts. This section focuses on five possible approaches in climate-smart computing, as summarized in Table 5, and discusses possible approaches for each.

### *4.1. Decarbonizing computing*

Computing itself consumes energy and produces substantial GHG emissions. As the demand for computing resources continues to grow, particularly with the expansion of data centers and other infrastructure, it becomes increasingly important to integrate environmental considerations (e.g., carbon footprint) into the evaluation of computing techniques.

***Sensors.*** Opportunities exist to reduce the carbon footprint of sensors. For example, sensors used in precision agriculture can be designed to leverage wind and solar power from the environment. This would help minimize their reliance on batteries, thereby reducing maintenance costs and environmental impact. Further energy savings can be achieved by optimizing sensor operating schedules with advanced edge machine learning algorithms [99]. These algorithms can dynamically adjust data collection frequency based on real-time analysis of soil moisture, weather forecasts, and crop requirements, ensuring that sensors are active only when necessary. Moreover, integrating predictive analytics with historical data and environmental conditions can optimize energy use across the entire sensor network, contributing to lower overall emissions. Finally, since the materials used in manufacturing sensors can themselves contribute to environmental pollution, developing environmentally friendly materials for sensors is crucial [100,101]. Biodegradable and recyclable materials can help mitigate their environmental impact.

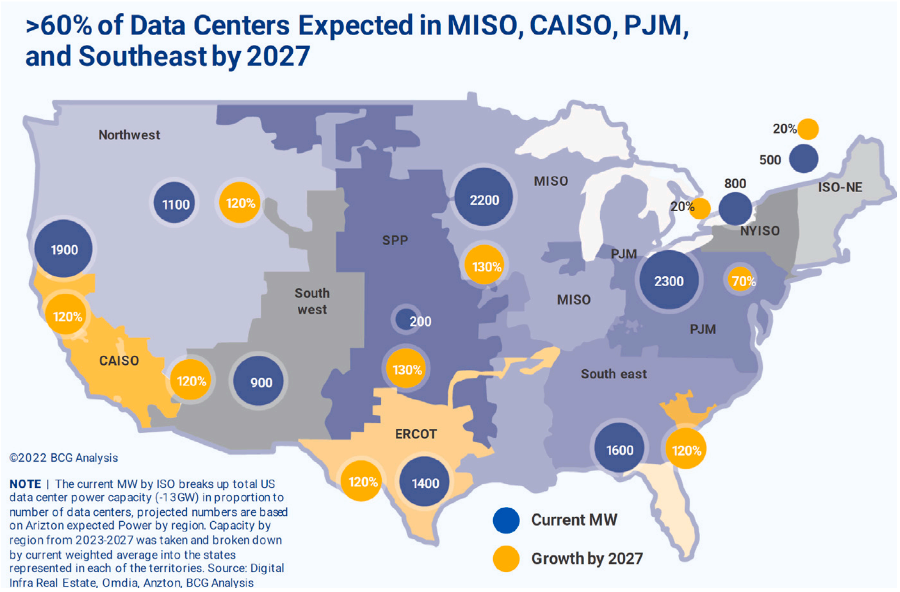



**Fig. 14.** Regional growth in electric demand due to data centers [98].

***Networks.*** During the data lifecycle, data will be replicated, migrated, deduplicated, and eventually archived or deleted. All these operations involve both storage and networking devices. Reducing emissions from computer networks presents significant challenges to computer science. There is a critical need to develop energy-efficient hardware, software, and algorithms. For example, in emerging 5G networks, dynamic strategies such as shutting down 5G radios, cell towers, and other equipment when not in use can significantly reduce energy consumption [102]. Additionally, energy-efficient packet routing can be achieved by shifting loads spatiotemporally to times and places with lower carbon footprints, optimizing the use of network resources based on the current energy grid's carbon intensity. Advanced time data analytics and predictive modeling leveraging data, including weather, grid load, and grid carbon intensity, can enable a more effective balance of energy supply and demand, seamlessly integrating renewable energy sources. These measures can reduce energy losses and GHG emissions while enhancing the reliability of the energy infrastructure. Furthermore, integrating blockchain technologies to create decentralized energy markets can allow consumers to trade surplus renewable energy, promoting a more sustainable energy ecosystem [103].

***Infrastructure.*** The growing awareness of the role that the emission of greenhouse gases (GHG) plays in climate change has motivated various industries to carefully monitor and plan for their GHG emissions. The electricity and heating sector has been a large contributor to GHG emissions, reaching over 40% of the total emissions in the world in 2021 [3]. Increased demand for data centers and other computing facilities is projected to be the largest driver of the growth in electric load in the US, amounting to a forecasted growth of 4.7% in peak demand by 2028 [98]. Fig. 14 illustrates the expected growth in electric demand by different regions in the U.S. This increasing demand underscores the importance of optimizing energy use in data centers to minimize their environmental impact. Effective strategies include optimizing energy consumption based on location and time-specific GHG intensities, integrating renewable energy sources, and improving the energy efficiency of computing infrastructure [104,105]. These measures are crucial to reducing GHG emissions from data centers and achieving sustainable growth in the computing industry.

Another major area of adaptation is the enhancement of cooling systems to handle higher temperatures. Traditional data centers consume vast amounts of energy for cooling. Adaptive solutions, such as utilizing ambient air in cooler climates or implementing advanced technologies like liquid cooling, can reduce energy consumption [106–108]. For example, Google's data center in Finland uses seawater for cooling, effectively reducing its energy consumption and environmental impact [109]. Smart computing could help further optimize these systems by predicting cooling demands using machine learning algorithms, thus reducing operational costs.

***Informatics.*** Optimally distributing the large-scale computations performed by data centers can significantly minimize GHG emissions while supplying the energy needed to run these data centers. This requires scalable multi-objective optimization of distributed computing algorithms. For instance, when training artificial intelligence (AI) models, the distribution of learning clusters can be determined based on factors such as operational cost, bandwidth requirements, and network latency tolerance [110]. GHG emissions can also be included in the optimization scheme, prioritizing data centers located in regions with low GHG-emitting energy sources, such as photovoltaic solar, wind, or storage, to handle more computation.

Another key computer science opportunity is the spatiotemporal scheduling of computing loads to take advantage of times and places with lower carbon footprints of electricity. This involves developing algorithms that dynamically shift computational tasks to data centers in locations and at times where the carbon intensity of the local power grid is lowest. Furthermore, climate-smart

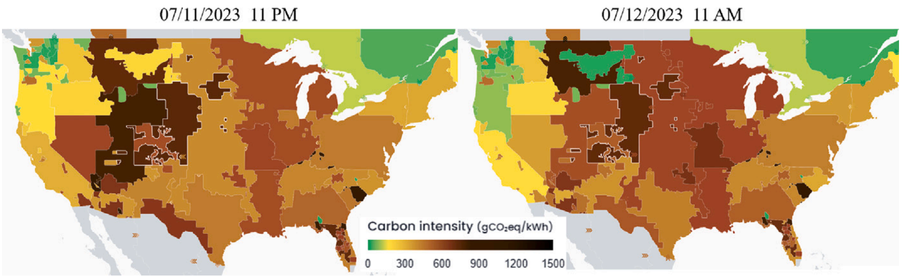



**Fig. 15.** Electrical grid marginal emissions rate data of US at different time stamps [113].

foundation models [111] can be developed to help reduce the cost of retraining informatics models from scratch, thereby reducing the emissions associated with large AI models. Selecting algorithms with lower emissions, such as opting for linear search instead of binary search when it results in lower energy consumption, can further reduce emissions.

***Optimization.*** A crucial requirement of all decarbonization efforts is a standardized means of measuring their effectiveness. Reductions in '$gCO_2eq$' (grams of carbon dioxide equivalent) measured at the source are valuable, especially when $CO_2$ is the primary emitted GHG. However, designing and deploying technology aimed at climate change mitigation requires an estimated measure of expected effectiveness. This estimate can be derived using models that simulate emissions generation. Such models are well-researched in sectors like transportation, where emissions models have minimal spatial dependencies. In the computing sector, the closest useful metric is the energy expenditure of running an algorithm. Kansal et al. [112] introduced the concept of 'energy complexity' to refer to the type and amount of computing resources used. Building on this, Jayaprakash et al. [67] proposed the idea of "carbon complexity", which provides an approximate emissions value by accounting for the carbon intensity of the local power grid and the energy complexity of running the algorithm. A simple and standardized metric of carbon complexity could offer a quantitative method for assessing the carbon footprint of various computational processes, enabling better-informed decisions aimed at reducing overall carbon emissions.

However, the marginal emissions rates from electrical grids (Fig. 15) indicate that GHG emissions rates from electricity generators vary by location and time. These regional and temporal variations challenge the i.i.d. (independently and identically distributed) assumption typical in traditional computing techniques, making the definition of carbon complexity more challenging. Developing methods to account for these variations is an essential computer science challenge in the quest to reduce the carbon footprint of computing.

### 4.2. Additional computing and its trade-offs

A key assumption in the applications of computing to societal sectors is that more computing is always better. However, it can be violated in the context of climate change, particularly for mitigation, as computing also has emissions. While increasing computing power and data availability can potentially reduce environmental impacts in various domains through targeted applications, the environmental costs of the computing and data infrastructure itself may simultaneously rise. Therefore, monitoring the climate costs associated with computing and data, and critically analyzing these tradeoffs, present important directions for future research.

#### 4.2.1. Short-term trade-offs

An illustrative example of the short-term trade-off between the benefits and costs of increased computing and data is presented in a recent study on the climate mitigation potentials of teleworking [114]. This study compared GHG emissions from working onsite versus from home, taking into account factors such as information and communication technology (ICT) usage, commuting, non-commute travel, and office and residential energy use. The main results (Fig. 16 [114]), show that while remote and hybrid work reduce energy consumption in offices and from commuting, it increases workers' ICT usage. Despite this increase in ICT usage, the study concludes that its effects on the overall carbon footprint are less significant compared to those of commuting and office energy consumption.

#### 4.2.2. Long-term trade-offs

As discussed in Section 3, increasing the use of computing and data can help reduce emissions across various domain applications over time. However, this process may exhibit the law of diminishing returns [115], meaning that while the initial reduction due to increased computing might be significant, the marginal savings in emissions may decrease as computing power continues to escalate. For instance, an accurate machine learning prediction model for farmland emissions is crucial for sustainable agriculture. Initially, adding more data to such a model can lead to substantial improvements in accuracy, resulting in greater emissions reductions. However, beyond a certain threshold, additional data may result in diminishing improvements due to factors like overfitting or the inherent limitations of the model. Moreover, more data and larger computational models will consume more energy. A conceptual illustration of such tradeoffs is given in Fig. 17. The green curve shows the diminishing returns in emissions reduction from computing and the downward-sloping cost function (red) represents the impact of additional computation. The net emission reduction (blue) rises initially but declines as returns diminish. From a long-term optimization perspective, an important research challenge is to identify the peak point in net emissions reduction.

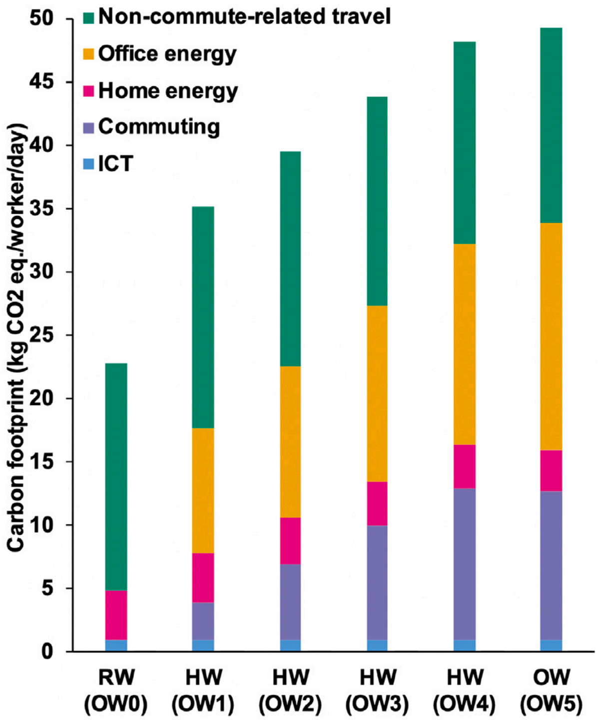



**Fig. 16.** Effect of remote and hybrid work on carbon footprint in the case of Microsoft. RW = remote work, HW = hybrid work, OW = onsite work. [114].

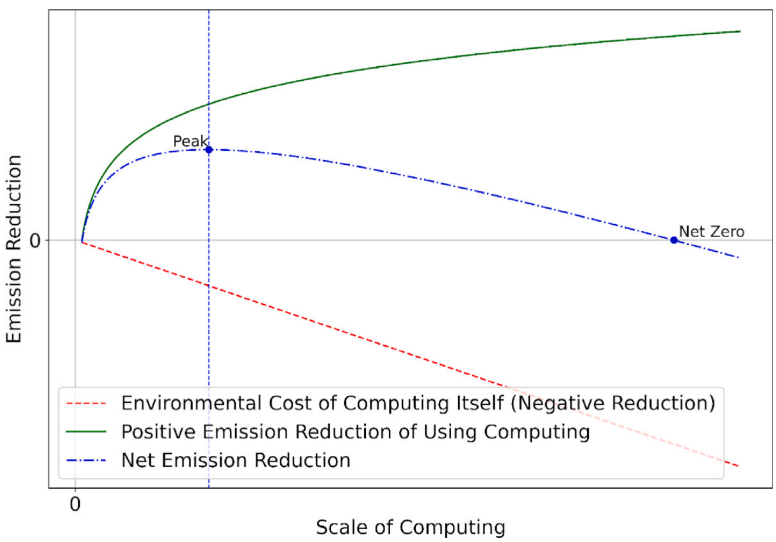



**Fig. 17.** A conceptual representation of the long-term tradeoff between the benefits and costs of computing with the scale of computing.

### 4.3. Climate resilient computing

As climate conditions become more extreme, ‘black swan events’ – rare and unpredictable occurrences that exceed current design specifications – are likely to become more frequent. Therefore, advancements in sensors, networks, and other computing infrastructure are essential to enhance their fault tolerance and reliability under harsh weather conditions. Improving the robustness of these systems will ensure continuous operation and minimize disruptions during extreme climate events. This includes developing resilient hardware, implementing adaptive algorithms, and creating redundant network architectures to prevent single points of failure.

***Sensors.*** Advancements in computing techniques are essential to achieve the "all places, all times" capability in sensors for climate resilience. Persistent intelligence in sensors can provide continuous, high-resolution measurements of the environment, crucial for detecting an early warning of climate extremes. Achieving this is challenging due to the vast geographic scale and the enormous volume of data generated. Persistent intelligence allows for real-time analysis and decision-making, transforming raw sensor data into actionable insights. This capability is vital for timely responses to climate threats, ultimately enhancing the resilience of communities and ecosystems to climate change.

Ruggedized sensors for agricultural applications, capable of withstanding extreme temperatures and humidity levels, exemplify this adaptation strategy. Smart computing can be used to provide alerts for maintenance and ensure continued operation under adverse conditions. Ensuring the availability of high-quality data and developing robust models to interpret this data are essential to improve climate understanding and inform decision-making.

***Networks.*** Networks play a crucial role in disseminating alerts and warnings following the detection of climate events. In this scenario, developing reliable sensor networks and communication systems remains a critical challenge. Example solutions may include using mesh topologies [116] and planning for redundancy in communication [117]. Other considerations include battery conservation, coverage, and latency [118]. Also, moving towards new cellular solutions such as 5G or NB-IoT can be another open topic, as the use of new cellular solutions specifically designed to support IoT devices and machine-to-machine communication could provide better coverage, battery saving, data rates, and latency performances in this context. Placing network infrastructure, such as routers and data centers, in areas less susceptible to climate impacts can also enhance resilience. Smart computing can use predictive models to analyze weather patterns and optimize the placement and redundancy of network infrastructure. Geo-redundant networks, which can reroute data in case of a local failure due to extreme weather events, illustrate the benefits of this approach.

Adapting to constantly changing climate conditions also requires flexible and scalable computing solutions that can quickly respond to new data and scenarios. This includes real-time monitoring and predictive analytics to foresee and mitigate impacts. Retrofitting existing computing infrastructure to adapt to new climate realities can be complex and costly. Developing modular and interoperable systems that can be easily updated is crucial to future adaptability.

### *4.4. Climate-scale computing techniques*

Traditional computing techniques are not designed to handle the tremendous volume, velocity, and variety of data collected by today's earth observation technologies. Therefore, there is a pressing need for innovative computing solutions that can process, analyze, and interpret this information effectively. Advancements in scalable and adaptive computing techniques are essential for improving our understanding and mitigation of climate change impacts.

***Simulation.*** One promising avenue is the development of higher-resolution climate models. Current global climate models typically operate at a spatial resolution of around 100 km, which limits their ability to capture fine-scale processes such as cloud formation and local land-atmosphere interactions. Advances in computing power, such as exascale computing systems, will enable the development of climate models with much higher spatial resolutions, down to a few kilometers or even sub-kilometer scales. These high-resolution models will provide more accurate simulations of regional climate patterns, extreme events, and the impacts of climate change on local ecosystems and human activities [119–121].

Additionally, the concept of digital twins is gaining traction in climate simulation. Digital twins are virtual replicas of physical systems that can be used to simulate and analyze complex scenarios in real-time [122]. By creating digital twins of Earth's systems, scientists can integrate real-time data with high-resolution models to monitor changes, predict future conditions, and develop mitigation strategies more effectively. This approach enables a dynamic and interactive way to study climate processes, allowing for continuous updates and improvements to the models based on the latest observations and data inputs.

***Infrastructure.*** There is an increasing need for more sophisticated computing infrastructure to meet the diverse computing requirements of climate research. For example, climate downscaling, which involves refining coarse-resolution climate model outputs to very fine resolutions beyond 1 degree, necessitates substantial computational power and storage capabilities [123]. High-resolution downscaling improves the representation of local climate features, which is essential for assessing climate impacts and developing adaptation strategies at regional and local scales. Combining multiple climate simulation models, also known as ensemble modeling, can enhance the accuracy and reliability of climate predictions by capturing a wider range of potential future scenarios and reducing uncertainties [124]. This approach requires advanced computing infrastructure to handle the increased data volume and computational complexity. As climate models become more detailed and sophisticated, the demand for high-performance computing systems, efficient data storage solutions, and robust data management practices will continue to grow, underscoring the importance of ongoing investment in climate-scale computing infrastructure [24].

The increasing availability of high-resolution satellite observations and in-situ measurements also presents opportunities for advancing climate understanding through computing. However, processing and analyzing these large datasets requires advanced data management and analysis techniques. Cloud computing platforms, such as Amazon Web Services and Microsoft Azure, provide scalable and cost-effective solutions for storing, processing, and analyzing large climate datasets. These platforms offer a range of tools and services, such as distributed computing, data analytics, and machine learning, that can be leveraged to extract valuable insights from climate data [121,125]. By utilizing these advanced computing resources, researchers can enhance their ability to manage and interpret extensive climate data, leading to improved models and more accurate climate predictions.

***Informatics***. Another important challenge in climate resilience research is designing efficient tools for identifying routes and schedules for large-scale evacuations in the face of natural disasters, such as hurricanes, wildfires, etc. This problem is computationally difficult because people are distributed across space and time, and multiple paths need to be managed concurrently. The capacity-constrained route planner (CCRP) [126], advances the concept of a time-aggregated graph to provide the earliest arrival time for any given start time.

In many cases, an evacuation scenario is accompanied by the need to allocate shelter to fleeing travelers. Given maps of an evacuee population, shelter destinations, and a transportation network, the goal of Intelligent Shelter Allotment (ISA) is to assign not only routes but also exits and shelters to evacuees for quick and safe evacuation. ISA is challenging due to movement conflicts and transportation network choke points [127].

Continued advancements in evacuation informatics are essential to address large-scale disaster response. For example, enhancing data availability is critical, as accurate estimations of evacuee populations and transport capacities will significantly improve the accuracy of evacuation models. Similarly, integrating detailed pedestrian data, such as walkway maps and link capacities based on their widths, is crucial for managing foot traffic during evacuations. In traffic engineering, refining link capacity models to reflect variations in traffic density and incorporating dynamic traffic control measures like signals, ramp meters, and contra-flow systems are pivotal for simulating emergency conditions more effectively. Understanding evacuee behavior at both the individual and household levels is also key. This involves tailoring evacuation strategies to accommodate diverse needs, including variations in physical ability, age, vehicle ownership, and language, which can optimize route and shelter assignments. Finally, evaluating the effectiveness of evacuation planning systems is paramount. It is important to develop robust methodologies that not only assess these systems under standard conditions but also challenge them to perform under extreme scenarios, pushing the boundaries of traditional evacuation models.

### *4.5. Interdisciplinary convergence*

Climate change is a dire societal problem that cannot be fully addressed by isolated paradigms in computing. Thus, systems thinking is needed to advance current computing techniques to efficiently incorporate data and knowledge from different domains, such as the physical and social sciences. Interdisciplinary integration enables a holistic approach to tackling climate-related issues by leveraging the strengths of various fields and fostering collaboration among scientists, engineers, and policymakers.

***Informatics***. An example of interdisciplinary convergence for climate understanding is the integration of machine learning techniques with physical models. Machine learning algorithms, such as deep neural networks, can be trained on large datasets of climate observations and model outputs to identify patterns, relationships, and uncertainties that may not be apparent through traditional statistical methods. These data-driven approaches can complement physical models by providing more accurate parameterizations of sub-grid scale processes, such as cloud microphysics and turbulence, which are difficult to represent explicitly in climate models. Furthermore, machine learning can be used to develop surrogate models that emulate the behavior of complex climate models, enabling faster simulations and uncertainty quantification [121].

Purely data-driven machine learning models have limited success in this task due to their large data requirements and their high estimation errors given the small amount of available training data [128]. Thus, research is needed to develop physics-informed informatics models that integrate physical information into machine learning models [129].

### *4.6. Responsible computing practices*

The consideration of responsibility in climate-smart computing is important due to potential harms related to lack of fairness, accountability, transparency, and other ethical considerations. For example, electric vehicle charging station sites chosen to maximize utilization may increase inequality, affecting fairness [130]. Similarly, the use of deep neural networks may hamper the transparency of decision-making.

Responsible computing practices are crucial in ensuring that advancements in computing technology contribute positively to climate understanding and mitigation. This involves not only the technical aspects of computing but also how information is communicated and utilized by diverse audiences, challenging the current assumption that accuracy is the main metric of model evaluation. Human-centered computing plays a significant role in this context, as it focuses on designing systems that are accessible, intuitive, and effective in conveying complex climate data to non-experts.

***Human-centered computing***. Climate data is often complex and multidimensional, making it challenging to convey to non-expert audiences. Advanced visualization techniques, such as interactive dashboards, immersive virtual environments, and augmented reality applications, can help make climate information more accessible and engaging to policymakers, stakeholders, and the general public. These tools can facilitate the exploration of climate data, the communication of climate risks and uncertainties, and the development of more informed and effective climate policies [119,120].

For disaster evacuation, it is crucial to develop strategies that build public trust and ensure compliance, deciding on the optimal timing for evacuations, the choice of routes, suitable modes of transportation, and shelter assignments are all vital considerations. Human-computing interaction (HCI) involves designing interfaces and communication channels that are intuitive and accessible to diverse populations, ensuring that critical information reaches all community members promptly. Effective HCI designs can support the delivery of timely and clear evacuation instructions via multiple platforms, including mobile apps, social media, public displays, and direct alerts. Additionally, HCI can facilitate interactive platforms where evacuees can provide feedback, report their status, and receive personalized guidance based on their location and circumstances. HCI also plays a role in post-evacuation analysis and improvement. By collecting user feedback and usage data, designers can refine the systems for better performance in future scenarios. This iterative process ensures that evacuation tools evolve based on real-world experiences and user needs.

Advances in HCI will likely be crucial for nudging consumers to adopt technologies that help mitigate climate change, most notably electric vehicles (EVs). A major hindrance in EV adoption is range anxiety — the uncertainty of how far an EV will run before requiring a charge. Colder climates and aggressive driving reduce EV range quickly, exacerbating range anxiety. A recent *New York Times* article highlighted the frustration of EV owners in Chicago as frigid weather diminished battery performance and significantly increased charging times [131]. Information about these factors, if presented in real-time, can help EV owners make informed decisions about charging and routing and reduce range anxiety. Interfaces that dynamically adjust the estimated range based on a driver's driving style are implemented in a wide range of EVs today. However, accuracy remains an issue with these calculations, especially when coupled with the effects of colder ambient temperatures. Algorithms that account for the effects of ambient temperature on EV range and also estimate battery performance for different driving styles, such as aggressive, moderate, and eco-friendly driving, can act as a valuable real-time feedback mechanism for consumers. Additionally, the UI could present possible re-routing options, including a detailed map of all nearby and in-route charging stations, their availability, and their respective wait times. This holistic approach ensures that EV owners have the necessary information to make informed decisions, thereby enhancing their confidence in EV adoption.

## 5. Conclusion and future work

Climate change is one of the most pressing societal challenges of our generation, affecting ecosystems, economies, and public health worldwide. Computing has a unique role to play, with applications that are already helping society understand climate change, mitigate its effects, build resilience, and support adaptation efforts. At the same time, climate data and processes often challenge traditional computing assumptions, posing significant challenges for the field in the years ahead.

This paper has outlined key areas where computing can contribute to climate-smart solutions, focusing on the themes of decarbonizing computing infrastructure, enhancing climate resilience, enabling large-scale data handling, fostering interdisciplinary approaches, and promoting responsible computing practices.

### 5.1. Key takeaways

The key takeaways of this perspective paper are summarized as follows:

- **Climate debate is still ongoing. However, common ground is emerging on resilience, economy, mitigation/adaptation win-win, etc.**
- **Computing is essential for managing climate change.** Across climate understanding, resilience, mitigation, and adaptation, computing provides essential tools to manage, analyze, and respond to climate-related data and challenges. PMC technologies such as nanosatellites and IoT devices have proven highly valuable for climate impact monitoring, real-time data collection, and localized climate adaptation efforts. These technologies offer comprehensive environmental monitoring across diverse and inaccessible regions, providing crucial data to improve climate models, track environmental shifts, and enable responsive adaptation interventions.
- **Computing can be decarbonized.** The growing energy demands of computing infrastructure contribute significantly to greenhouse gas emissions. PMC technologies, including mobile networks and IoT devices, have become significant contributors to computing emissions due to their extensive deployment and power requirements. Efforts to decarbonize computing include optimizing energy usage, incorporating renewable energy sources, and implementing advanced cooling solutions. Research into energy-efficient algorithms, carbon-aware scheduling, and distributed computation will also be vital for reducing emissions and supporting sustainable computing growth.
- **Climate modeling requires better integration of diverse data.** Climate data integration poses unique challenges due to the high volume and diverse sources, including satellite sensors, weather stations, and large-scale climate simulations. Effective frameworks are needed to manage this heterogeneous data, supporting real-time processing and integration into predictive models. These advancements can improve forecasting accuracy, allowing for timely responses to climate threats. Additionally, distributed computing and cloud platforms are essential for handling large climate datasets, enabling scalable and collaborative research efforts.
- **Computing systems must be made climate-resilient.** Climate change brings an increase in extreme events, requiring resilient computing systems that can withstand and adapt to these stresses. PMC technologies play an essential role in building climate resilience by supporting early warning systems and real-time monitoring. This includes advancements in fault-tolerant hardware, robust sensor networks, and adaptive algorithms capable of operating in harsh conditions. Key examples are climate-resilient infrastructure for data centers, geographically redundant networks to handle data rerouting during local failures, and predictive analytics that support climate resilience planning. Additionally, climate-resilient computing infrastructure needs to be modular and interoperable to allow for efficient updates and adaptability as climate conditions evolve.

- **Climate-smart computing cannot be achieved without interdisciplinary collaboration and responsible practices.** Effective and holistic climate solutions require cooperation across disciplines, leveraging insights from computing, environmental and other physical science, social science, and policy. This approach enhances climate understanding, improves mitigation strategies, and supports comprehensive adaptation planning. Responsible computing is also crucial, ensuring fairness, transparency, and equitable access to technology. Human-centered computing designs can improve the accessibility of climate data for diverse populations, while ethical considerations guide decisions about data privacy and environmental justice. Interdisciplinary and responsible computing efforts aim to ensure that climate solutions are both scientifically rigorous and socially beneficial.

### 5.2. Emerging research priorities

As computing evolves to address climate change, we see several urgent research needs emerging.

- **Prioritizing Emissions Reduction and MRV in Pervasive Computing:** Given the environmental impact of pervasive and mobile computing technologies, emissions reduction and measurement, reporting, and verification (MRV) [132] are essential research areas for the PMC community. Developing methodologies for accurate and scalable MRV and exploring efficient architectures and energy-saving designs are high-priority areas. Reducing the emissions of pervasive computing infrastructures, while maintaining their effectiveness for climate adaptation and mitigation, is a complex but necessary challenge.
- **Energy-aware AI Models:** The rapid growth in large AI models is driving a notable increase in data center energy demands. Research is needed to understand, measure, and mitigate the energy consumption associated with AI training, inference, and deployment. Solutions could include optimizing algorithms for energy efficiency, developing energy-aware AI frameworks, and exploring alternative computing architectures to reduce energy needs without compromising performance. To counteract Jevons' Paradox [133] – the phenomenon whereby increased efficiency can lead to higher overall energy use – future research should also consider strategies that also limit the extent of resource-intensive AI activities.
- **Probing the Benefits and Costs of Increased Computing and Data Collection:** The growth of computing and data for climate applications brings both significant benefits and considerable environmental costs. Future research must assess and balance the trade-offs between increased data collection and computational power (for applications like climate modeling, real-time monitoring, and predictive analytics) against their energy demands and emissions footprint. Balancing these factors is crucial for sustainable development in climate-smart computing, especially as data and computing needs expand.

We urge the computing community to engage deeply with climate-related topics, as there is much we can do to advance solutions for climate mitigation, resilience, and adaptation. Educators should integrate climate topics into computing curricula to foster a new generation of climate-aware computing professionals, and funding agencies should prioritize research that addresses these urgent challenges.

## CRediT authorship contribution statement

**Mingzhou Yang:** Writing – original draft. **Bharat Jayaprakash:** Writing – original draft. **Subhankar Ghosh:** Writing – original draft. **Hyeonjung Tari Jung:** Writing – original draft. **Matthew Eagon:** Writing – original draft. **William F. Northrop:** Writing – review & editing. **Shashi Shekhar:** Writing – original draft.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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**Table A.6**
Table of Acronyms.

| Acronym | Definition |
|---|---|
| PMC | Pervasive and mobile computing |
| GHG | Greenhouse Gas |
| IPCC | Intergovernmental Panel on Climate Change |
| AI | Artificial Intelligence |
| IoT | Internet of Things |
| HVAC | Heating, Ventilation, and Air Conditioning |
| ML | Machine Learning |
| HPC | High-Performance Computing |
| TEG | Time-Expanded Graphs |
| CCRP | Capacity-Constrained Route Planner |
| ISA | Intelligent Shelter Allotment |
| TAG | Time-Aggregated Graph |
| RCM | Regional Climate Model |
| ISM | Ice Sheet Model |
| ECM | Engine Control Module |
| V2G | Vehicle-to-Grid |

**Table A.7**
Glossary of key terms.

| Term | Definition |
|---|---|
| Greenhouse Gases | Gases in Earth's atmosphere that trap heat, such as carbon dioxide, methane, nitrous oxide, and fluorinated gases, contributing to the greenhouse effect. |
| Net Zero | The balance between the amount of greenhouse gas emissions produced and the amount removed from the atmosphere, achieving no net increase in atmospheric GHG levels. |
| Global Warming | The long-term rise in the average temperature of the Earth's climate system, primarily due to human activities such as burning fossil fuels and deforestation. |
| Climate Change | Long-term changes in temperature, precipitation, and other climate conditions on Earth. |
| Climate Understanding | Comprehending the drivers of planetary processes and projecting how these processes might change under various scenarios, such as increased greenhouse gas emission |
| Climate Resilience | The ability of a social, ecological, or socioecological system and its components to anticipate, reduce, accommodate, or recover from the effects of a hazardous event or trend. |
| Climate Change Adaptation | The process of adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderate harm or exploit beneficial opportunities. |
| Climate Change Mitigation | Human interventions to reduce the source of greenhouse gas emissions and protect natural carbon sinks. |
| Industrialization | The process of developing industries in a country or region on a wide scale, often leading to increased greenhouse gas emissions. |
| Phenological Shifts | Changes in the timing of seasonal biological events such as flowering, migration, and breeding, often influenced by climate change. |
| Scenario Simulation | Using models to predict and analyze the outcomes of different hypothetical scenarios, often used in planning for climate resilience and adaptation. |
| Risk Assessment | The process of identifying and evaluating the potential adverse effects of climate-related events on various sectors and systems. |
| Regional Climate Model | A type of climate model that focuses on specific regions of the world, providing more detailed climate predictions than global models. |
| Vehicle-to-Grid | A system that allows electric vehicles to communicate with the power grid, storing excess energy and supplying it back to the grid when needed. |
| Time-Expanded Graphs | A mathematical representation used in network flow problems, where the network is duplicated for each time point to simulate the passage of time. |
| Precision Agriculture | A farming method that uses sensors, GPS, and data analytics to optimize crop management by recognizing soil's spatial variability, improving resource efficiency and productivity. |
| Decarbonize | The process of reducing carbon dioxide and other greenhouse gas emissions resulting from human activities, particularly through the adoption of renewable energy sources, energy efficiency measures, and sustainable practices. |
| Responsible Computing | The practice of developing and using computing technologies in a manner that ensures fairness, accountability, transparency, and ethical considerations. |

## Appendix. Tables

See Tables A.6 and A.7.

## Data availability

No data was used for the research described in the article.

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