ABSTRACT

Among the seventeen Sustainable Development Goals (SDGs) proposed within the 2030 Agenda and adopted by all the United Nations member states, the 13th SDG is a call for action to combat climate change for a better world. In this work, we provide an overview of areas in which audio intelligence – a powerful but in this context so far hardly considered technology – can contribute to overcome climate-related challenges. We categorise potential computer audition applications according to the five elements of earth, water, air, fire, and aether, proposed by the ancient Greeks in their five element theory; this categorisation serves as a framework to discuss computer audition in relation to different ecological aspects. Earth and water are concerned with the early detection of environmental changes and, thus, with the protection of humans and animals, as well as the monitoring of land and aquatic organisms. Aerial audio is used to monitor and obtain information about bird and insect populations. Furthermore, acoustic measures can deliver relevant information for the monitoring and forecasting of weather and other meteorological phenomena. The fourth considered element is fire. Due to the burning of fossil fuels, the resulting increase in CO\textsubscript{2} emissions and the associated rise in temperature, fire is used as a symbol for man-made climate change and in this context includes the monitoring of noise pollution, machines, as well as the early detection of wildfires. In all these areas, computer audition can help counteract climate change. Aether then corresponds to the technology itself that makes this possible. This work explores these areas and discusses potential applications, while positioning computer audition in relation to methodological alternatives.

Keywords  Computer audition, audio intelligence, climate change, earth, water, air, fire, environment, call to action
1 Introduction

Our climate is rapidly changing. According to the 2021 Assessment Report of the International Panel for Climate Change (IPCC): “Human influence has warmed the climate at a rate that is unprecedented in at least the last 2000 years” [Masson-Delmotte et al., 2021]. CO₂ emissions caused by human activities are a major driver of those changes, and have caused a dramatic rise in temperatures from the mid 19th century to the present day [Masson-Delmotte et al., 2021]. This rise in temperature has impacted the environment in various ways: increased precipitation, rise of sea levels, loss of glacier mass, desertification, heatwaves, and an increased frequency of extreme weather events [Masson-Delmotte et al., 2021], with those changes in turn leading to a massive loss of natural habitats and biodiversity [Hoegh-Guldberg and Bruno, 2010, Ceballos et al., 2017]. These extraordinary circumstances are also detrimental to human well-being and health [Watts et al., 2015], compromise food security [Wheeler and Von Braun, 2013], and lead to increased armed conflicts [Raleigh and Urdal, 2007].

Accordingly, climate change has been described by many as ‘the greatest challenge of our time’, calling for an equally outstanding response by the international community. Efforts at governmental and institutional level to curb CO₂ emissions and limit environmental pollution have largely dominated public conversations, and rightfully so, as a coordinated push towards transforming our societies is paramount to mitigating the more catastrophic effects of climate change. To that end, major focus has been placed on regulating polluting activities. In many respects, this can be seen as a move to limit the use of certain polluting technologies across several facets of human activity. Future technological breakthrough, however, is expected to play a major role in curbing, and even reversing, emissions, for example through the development of renewable energy sources [Panwar et al., 2011] and carbon sequestration technology [Figueroa et al., 2008].

Artificial intelligence (AI) is one of those technological paradigms with a great potential for assisting the fight against ecological catastrophe [Cowls et al., 2021]. Its major promise comes from the capacity to analyse vast amounts of diverse, multi-dimensional data and the ability to enable distributed, localised interventions in ecosystems in need. AI can be used in two major ways with respect to climate change: to understand it and to combat it. Understanding corresponds to the detection and categorisation of patterns; this could be (global or local) weather patterns, the tracking of specific environmental indicators, or the monitoring of animal populations. Combating, in turn, aspires to utilise AI-powered technologies to counteract specific changes. This differentiation is consistent with the common categorisation of AI systems into those that passively observe and those that actively interact with their environment.

Computer audition (CA) is the sub-field of AI that encompasses all facets of the auditory information stream; it can thus function both as a passive perception system and an active, audio-generating agent. Even though CA plays an important role within the AI community, its potential for helping combat climate change remains largely untapped. The aim of this article now is to highlight application areas where CA can be utilised in this context.

The catastrophic effects of climate change are spread over different parts of our planet’s natural ecosystem, the diverse characteristics of which warrant for specialised considerations for any technology that purports to be utilised in the fight to protect them. In our attempt to categorise the different application areas for which CA can be useful, we adopt the four element theory proposed in Ancient Greek and Persian mythology [Partington, 1989]: earth, water, air, and fire, a quick overview of which is provided in fig. 1. Earth and water concern themselves with terrestrial and aquatic ecosystems. Air stands for applications targeting gas monitoring, bird and insect population monitoring – in a nutshell, everything that exists in our planet’s atmosphere. Fire is used in both a metaphorical and a literal sense: as the biggest threat to our environment is the rise of temperature caused by CO₂ emissions, starting with the invention of the internal combustion engine, we use fire as a symbol for all those human activities that threaten our environment; but (wild)fire in itself is also a big threat to earthly ecosystems, so we also accordingly analyse how CA can assist in its detection and mitigation.
This leaves *aether*, a fifth element proposed by Aristotle which constitutes the ‘essence of things’, as a symbol for AI, the enabling technology making a variety of innovative approaches possible. The word itself calls attention to the popular depiction of AI-powered systems as magical solutions for several types of problems – a fallacy we attempt to avoid by sketching out extrapolations of existing, well-founded approaches, that may lead to the realisation of the promise of CA to assist in climate change mitigation, as well as highlighting associated challenges.

To date (as of 21 December 2021), there are 321,776 articles indexed in the Web Of Science Core Collection related to climate change (search term: “climate change”), with its number having triplicated over the last 10 years (13,678 in 2012 vs 39,595 in 2021). 2,571 of these articles deal with AI (search term: “climate change” AND (“artificial intelligence” OR “machine learning” OR “deep learning”)) and were to a large part (76%) published in the last three years. With a total amount of just 89 Web of Science Core Collection indexed articles (search term: “climate change” AND (“artificial intelligence” OR “machine learning” OR “deep learning”) AND (audio OR acoustic* OR sound OR noise)), CA has played a minor role in research on climate change so far. However, same as for AI in general, there has also been a significant increase of CA-related articles in context of the climate change in recent years. 45 of the 89 articles were published in 2020 and 2021 (see fig. 2).

These numbers indicate that CA represents a relatively underexplored, but promising field for fighting climate change. In the following, we give a comprehensive, but non-exhaustive overview of important recent work using CA in order to assist our planet. For this overview, identified relevant studies were categorised according to application areas. In this regard, each of the following sections is dedicated to one application area represented by the previously introduced elements earth, water, air, and fire, followed by more general AI-related aspects being addressed in a section on aether. As the opposite of recording and automatically analysing audio, we then also outline the idea of intelligent audio generation to help the ecosystem, in a separate section. Finally, we discuss the advantages and limitations of CA compared to alternative methodology at hand to help the environment; we address relevant ethical issues, and close by providing an outlook of what has been reviewed in this paper.
2 Earth

This section deals with the first element, earth, and discusses the potential CA has to combat climate change in this setting. In doing so, we focus on the recognition of changes on earth at an early stage [Martin et al., 2008], which is of great importance in order to avert potential damage, and therefore to be able to react in good time and to protect living beings accordingly.

2.1 Environmental Changes

The detection of environmental changes is a crucial component of future challenges [Martin et al., 2008]. As these environmental changes are becoming increasingly rapid and have an impact on many areas of life, it is important that these changes are identified at an early stage so that appropriate countermeasures can be taken. Environmental changes can be natural changes, such as natural disasters in the form of earthquakes or volcanic eruptions [Banholzer et al., 2014, Hallegatte, 2016], but also man-induced changes [Hansen and Sato, 2012], like deforestation. Both types of changes must be recognised at an early stage so that appropriate mitigation strategies can be planned.

While previous methods for environmental change detection primarily use visual data [Kim et al., 2019, Liu et al., 2016], CA offers the possibility to use a new, so far largely untapped, information channel. With this new possibility of hearing environmental changes, several sounds can be perceived. One category are man-induced changes [Hansen and Sato, 2012], such as deforestation of the rainforest. In this case, e. g., the detection of chainsaws or large machines can serve as an indicator. Another category is the detection of natural events [Banholzer et al., 2014, Hallegatte, 2016]: environmental changes, such as earthquakes, cause perceptible sounds to various natural objects, which can also be heard with special devices [Müller et al., 2015].

2.2 Animal Population

CA was already used to classify several animals in the past [Gibb et al., 2019, Stowell et al., 2019, Schuller et al., 2021]. The availability of audio recordings over a wide area could not only identify which animals are present in the region, but also roughly how many of them are present and where they are moving. Animal monitoring with CA can therefore be a great opportunity [Gibb et al., 2019]. Big changes in the movement of animals could, e. g., indicate possible dangers such as natural disasters [Garstang and Kelley, 2017]. All of this can be detected without having seen a single image of the actual danger, but only with the audible movement profile of the animals.

By detecting which and how many animals are at a given location and where they are moving to, animal movement profiles can also be used to analyse their population dynamics at different locations. If the population of certain animals...
at a location decreases sharply, this can be used as an early warning system to take countermeasures in time. This not only provides insight into the evolution of species in different locations, but also the opportunity to save endangered species from extinction through early interventions.

In addition, animals produce diverse sounds in nature, such as when defending territories, fighting with other animals, or during mating season [Blumstein et al., 2011]. With the help of these sounds, biologists can gain a variety of valuable insights into the animals’ way of life and use this information for further analyses. Moreover, the automatic characterisation of biological traits in animals, such as by sex and age groups, can help monitor the health of packs and herds in the wild [Blumstein et al., 2011].

Another major problem of our time is the change in biodiversity and species extinction. This is again an area where CA can add value [Gibb et al., 2019]. It is a great advantage to be able to cover extensive areas with microphones to gain insights over animal population. Audio recordings are particularly useful in places where it is difficult to make full-coverage camera recordings, such as in forests. Furthermore, the presence and composition of different acoustic sounds provides information not only about the composition of vocalising species and the orthopteran species richness, but also about the structure of the landscape and the intensity of land use [Müller et al., 2022].

2.3 Animal Protection

In addition to the previous section, not only the movement profile of animals can be used as an indicator for dangerous changes, but this information can also be combined with directly perceptible sounds, such as machinery sounds which indicate the presence of humans. Therefore, such a fully comprehensive audio understanding allows early detection of environmental changes and thus danger for the animals that might otherwise have gone undetected.

Nature is not the only source of danger to animals; they can also pose a danger to one another or danger is posed by human beings. For example, poachers pose a threat to wild animals and predators to farm animals, such as livestock or poultry. CA can be of benefit here as well, such as by recognition of gunshots [Turian et al., 2022].

In agriculture, attack by wild animals is often a major hazard. Several solutions have therefore already been developed in the field of computer vision to detect relevant situations [Andavarapu and Vatsavayi, 2017]. Nevertheless, visual solutions have the problem that cameras usually cannot fully cover large pastures. In contrast, CA offers the advantage that audio recordings of large pastures can be fully recorded with only a few microphones and are therefore much more suitable for practical use cases. These audio recordings can then be used to determine which animals are in the pasture.

In case of an attack on the herd by wild animals, this knowledge can be used to inform the farmer accordingly in time. An attack by humans on animals, e.g., by poachers, can also be heard and detected at an early stage, thus, endangered animals can be protected from other animals as well as from humans [Kamminga et al., 2018].

In this respect, the recognition of emotion and social (and more general cognitive, physical, and health) state of animals by audio [Hantke et al., 2018] can also help monitor their health and wellbeing or recognise impeding threats.

2.4 Plant Bioacoustics

On a different note, the field of plant bioacoustics is a rising exploration field which focuses on the sound waves created by plants and insects. Bioacoustic tools have been applied to measure mechanical properties of plant structures, optimise mechanical harvesting, and detect the distribution of root systems, as well as to monitor plant health, photosynthesis, and ecology [Khait et al., 2019]. Recent experimental studies open the possibility of assessing the stress of plants by using machine learning algorithms on acoustic signals, e.g., analysis of ultrasound emitted by plants to determine their health [Mankin et al., 2018].

In addition, acoustic and vibration sensors are used by entomologists to detect hidden infestations of invasive insect species, and to monitor insect movement, feeding, and mating activities on host plants [Cocroft and Rodríguez, 2005]. Novel studies [Mankin et al., 2018] consider the use of bioacoustic tools to analyse plant health and structural
characteristics, and discuss how combinations of spectral-, temporal-, and spatial-distribution features of signals detected in plants can be interpreted in ways that properly enable reliable assessment of hidden pest infestations, including invasive insect species of importance for plant biosecurity.

The acoustic performance of some organisms show the magnification of the effects of climate change. Drought, for example, produces stress on trees and leads to an increased vulnerability to insect attacks. Insects are drawn to stressed trees using chemical signals, but also are attracted by the sounds emitted by tree cells [Krause and Farina, 2016]. These sounds, which are produced by forest trees when being under drought stress, are known as cavitation, which is the result of cells collapsing by gradual dehydration. The majority of these sounds emitted are within a frequency range of 20 kHz to 200 kHz [Gagliano et al., 2012] and carry information for insects, that can perceive such signals.

Defoliating insects have a large impact on ecosystems and are influenced by climate change as well [Pureswaran et al., 2018]. Therefore, changes of their behaviour can be used as an indicator of e.g., an increasing amount of CO$_2$ in the atmosphere. Early detection of these changes is of great importance. Thus, this acoustic feedback from insects can have a positive effect, as it can be detected by CA and thus indicate defoliation, forest decline, and CO$_2$ increase. Insects will be addressed in more detail in the section on air.

3 Water

Water is often referred to as the ‘element of life’. It serves as nutritional source [Popkin et al., 2010; Ritz and Berrut, 2005; Self and Waskom, 1992], as a habitat for various animals [Alava et al., 2012; Samuel et al., 2005; Freeman et al., 2013] or can simply be used to maintain hygiene and therefore avoid several diseases [Mara, 2003; Ashbolt, 2004; Pengpid and Peltzer, 2012; Curtis, 2007; Matta and Kumar, 2017]. That is, every living being on our planet needs water to survive. Therefore, we have to ensure the quality and quantity of this vital source of life.

Water can be encountered in three physical states: solid, liquid, and gas. Thus, we have by default various ways to perceive this element. For instance, considering its solid state, ice, CA could hear the cracking ice long before we could observe it melting visually, e.g., when chunks of ice break down from icebergs or glaciers are disappearing; which might be indications of an increasing temperature in the environment. CA also has the potential to detect possible hazards like floods or tsunamis early on or to monitor the water supply of an area. Besides, coral reefs, which are often called the “rainforests of the sea” [Knowlton, 2001], and its biodiversity can be tracked. Regarding animal observation, the animal communication and movements can be investigated quite easily with CA. It is much more efficient to record related sounds with microphones under the water surface covering a larger area than, for example, diving in with cameras. In water, sound propagates with a higher velocity and over greater distances than in air. This is conversely to vision, which is dramatically hindered in water as compared to travelling through air. In the following subsections, these various application areas will be described in more detail.

3.1 Melting Ice

In times of melting polar ice caps it would also be helpful to monitor the process of the melting ice. That is, we can hear for cracking sounds in icebergs, ice floes or glaciers [Urick, 1971; Ashokan et al., 2016; Lee et al., 2013]. If there is an accumulation of cracking noises or a huge explosive crack it might be a clue for the melting of ice which is affected tremendously by increased temperatures and, thus, an indicator of climate change. On the one hand, the detection of melting ice can be important for study purposes, e.g., to investigate how long the melting process has lasted before a chunk of ice breaks down from a glacier [Deane et al., 2019]. On the other hand, it can be utilised for the early prediction of avalanches or floods and, therefore, enable precautions or appropriate countermeasures. In the best case, catastrophes could even be prevented.

Moreover, there can be major landslides due to melting glaciers causing enormous landslides and tsunamis [Marchenko et al., 2012; Higman et al., 2018]. According to researchers, there is a ticking time bomb at the moment in Alaska
within the Barry Arm area, the Barry glacier, which has the potential of causing a mega-tsunami [Dai et al., 2020]. Moreover, the risk of major landslides due to melting glaciers and, thus, the risk of arctic mega-tsunamis is rising steadily [Schiermeier, 2017].

3.2 Floods

But not only the sound of cracking ice might be helpful in predicting floods or flood waves, but also the sound of flowing water (e.g., in rivers), since this sound reflects the water flow velocity [Tonolla et al., 2009, Lumsdon et al., 2018]. The sound is generally generated by particle collisions through streamed sediment movements as well as the flow of water over submerged obstructions [Lumsdon et al., 2018]. These factors might be very helpful for roughly inferring the amount of flowing water and predicting overflowing rivers and lakes in order to appropriately prepare agricultural land and the surrounding civilisation for such scenarios. In this connection, hydrophones – underwater microphones – could be placed at locations, which have a high potential of being hit by floods such as estuaries at glaciers, water reservoirs, or moors.

3.3 Water Supply

In addition to the early prediction of floods due to the sound of running water we can also predict the opposite. That is, if there is minimal audible sound it might be a clue for drying up rivers, lakes or natural fountains, and thus be a sign of water shortage in a certain region. Via early prediction of water scarcity in specific areas, artificial irrigation facilities could be constructed in advance or the people living in such areas could be relocated.

However, water supply does not only apply to overall regions but also to individual beings. To that end, we can exploit the fact that all living beings contain water in their bodies. For instance, based on ultrasonic sounds of trees, their water supply could be assessed and conclusions about their water supply could be drawn [Ponomarenko et al., 2014].

3.4 Maritime Life

Soundscapes have been used in terrestrial landscapes and restoration, and are recently being used to monitor coral reefs underwater [Lin et al., 2021]. In places where dynamite fishing is common practice, the reefs end up being destroyed [Slade and Kalangahe, 2015, Wells, 2009]. Such endangering human activity can of course be automatically heard. In addition, due to rising sea temperatures and the acidification of the oceans, mass ‘bleachings’ of coral reefs is now a common occurrence. A healthy coral reef can be distinguished through the acoustic modality, as their bright, loud, and diverse soundscapes guide the recruitment of reef organisms, but those disappear when damage occurs [Lamont et al., 2021]. Restoring the reefs can bring those sounds back to life, as well as the ecosystem [Lamont et al., 2021]. Besides, the acoustic enrichment consequence of generating and emitting sounds from such healthy soundscapes underwater can enhance fish community development on degraded coral-reef habitats [Gordon et al., 2019].

By sensing underwater animal sounds, e.g., produced for communication purposes or caused by movement patterns, conclusions can be drawn w.r.t. their population, behaviour, and habitat [Clark and Johnson, 1984, Cummings and Holliday, 1987, Klinck et al., 2012, Schuller et al., 2019]. Large bioacoustic archives like the Orche [Ness and Tzanetakis, 2014, Ness et al., 2013] are very useful in this context [Bergler et al., 2019].

The aforementioned scenarios can be significantly influenced by changing environmental conditions. Therefore, they are key factors in which to measure the repercussions of climate change, fight its consequences, and tackle the damage caused by humans.
4 Air

The mass of air that we denominate the atmosphere represents approximately only the 5% of the total volume of our planet, but it is crucial for all forms of life in it. CA can make a big impact in the sustainment of both natural and human-made environments through air as it is – from a human perspective – the common medium for the propagation of sound waves.

In the wild, the atmosphere supports a thriving ecosystem for birds, bugs, and bacteria. Acoustics can have a big impact in habitat monitoring by tracking birds migration and insects populations. Audio information can also be used for the efficient administration of crops by controlling and monitoring pests. Besides, acoustic measures can give us relevant information for weather and meteorological effects monitoring and forecasting, such as air pressure measures and wind characterisation [Chide et al., 2021]. Gathered data can be used from the predication of overcast and sunlight ratios for enhancing agriculture production sustainability, to the prediction of natural disasters such as tornadoes [Elbing and Petrin 2018]. In this section, we will discuss more in depth, where CA in connection with air can make a contribution to save the planet.

4.1 Aerial Life

The atmosphere and the earth’s ecosystems are parts of a coupled system. The disciplines of aerobiology and aeroecology explore how animals, plants, and other organisms live in, move through, and interact with the atmosphere.

Birds are rapidly affected by changes in the environment. In the mining industry, caged canaries were carried down by miners into the mine tunnels. Whenever there was a leak of dangerous gases, such as carbon monoxide, the gases would kill the canaries, which served as a warning for the miners to exit the tunnels immediately. Birds are messengers that tell us about the health of the planet because they are widespread, they connect habitats, resources and biological processes. They also contribute to ecosystem services – as natural enemies of pests, pollinators of fruit, and seed transporters [Whelan et al., 2008]. Birds also play a key role in cycling nutrients and helping to fertilise marine ecosystems [Plazas-Jiménez and Cianciaruso, 2020]. They are thus crucial for the sustainability of the environment.

Whether ecosystems are managed for agricultural production, wildlife or water, success can be measured by the health of birds. Bird sound classification aids to determine their presence, tracking their migrations, and measuring their population [Pillay et al., 2019, Stowell et al., 2019]. A decline in bird numbers informs about a damaged environment [Sekercioğlu et al., 2004], e.g., due to habitat fragmentation and destruction, pollution, and pesticides introduced species, etc. Birds provide insect and rodent control, which results in tangible benefits to people. Insect outbreaks can annually have a huge negative economic impact in agricultural and forest products, and some birds can be effective to substantially reduce insect pest populations without the health, environmental, and economic risks of harmful pesticides [Initiative, 2009]. Microphone arrays can give us bird data in a continuous manner, where other sensors such as cameras would struggle to monitor such large areas. For instance, for the tracking of nocturnally migrating birds [Bardeli et al., 2010], for which the use of night vision cameras – requiring complex manufacture with high-voltage power supplies to operate – would be expensive. The acoustic performance of bird communities reaches its maximum at dawn and dusk, when species are contemporarily singing and producing choruses [Farina et al., 2015]. Measuring the length, energy, and frequency components of choruses can, e.g., give insight about the ambient temperature [Hasan and Badri, 2016], as ambient temperature can cause changes in the physiology of organisms.

4.2 Insects and Pests

In addition to birds, insects are the other large group of species that populate the air. They are under immense pressure from land use intensification and climate change effects, threatened with extinction or showing significant population declines [Sekercioğlu et al., 2012]. Insects are essential in food chains and cycles; they pollinate fruits, flowers, and vegetables, and are also very important as primary or secondary decomposers. Many insects are omnivorous, and eat
a variety of foods including plants, fungi, dead animals, and decaying organic matter, helping breaking down and disposing wastes. Predatory or parasitic insects help keep pest populations, such as insects or weeds, at a tolerable level. They are also the sole food source for many amphibians, reptiles, birds, and mammals.

Especially, bees contribute to complex, interconnected ecosystems that allow a diverse number of different species to co-exist. Acoustical non-intrusive sensors are being introduced along with temperature and moisture sensing for bee hive colony activity health and status monitoring, for its subsequent analysis using machine learning. In recent decades, acoustic devices have provided nondestructive, remote, automated detection and monitoring of insect and pest infestations for pest managers, regulators, and researchers. Microphones are useful sensors for airborne signals, specially ultrasonic sensors, which are particularly effective for detecting wood-boring pests like termites at frequencies of more than 20 kHz.

Insect pests can also pose a serious threat to agricultural and forest ecosystems, but the difficulty to control insect pests makes them challenging to prevent. Novel research on methods for acoustic data analysis based on active sound production by larvae (i.e., stridulations) can give insight into larval ecology produced by pests and opens up a new road for pest control. This acoustic monitoring of larvae, and the data analysis for automatically detecting audio sections with stridulations, can provide an estimate of their activity, enabling non-invasive species-specific pest monitoring.

As reliability and ease of use increase and costs decrease, acoustic devices have considerable future promise as cryptic insect detection and monitoring tools.

4.3 Meteorological Phenomena

The movement of winds have huge implications for storm systems and precipitation patterns. Specifically, westerlies winds transport dust from desert regions to faraway locations, making changes in the environment. Recording aeroacoustic noise generated by wind flowing past a microphone can provide wind speed and wind orientation. A recent study analysed the frequencies composing the wind-induced acoustic signal measured by microphones. The acoustic spectra recorded under a wind flow can be decomposed in the low-frequency range, mainly reflecting the wind velocity, and the higher frequency range, regarded to depend on the wind direction relative to the microphone. Therefore, microphones as tools to monitor the wind have a huge potential to show climate disruptions and potentially help adaptively control energy-generating wind mill farms, while also hearing potential disruptions in their routine.

On a different note, numerous geophysical and anthropogenic events emit acoustic waves below the human hearing range of about 20 Hz, i. e., infrasound, including hurricanes and tornadoes. The rate of increase of severe storm environments becomes greater in the northern hemisphere due to temperatures rises. Tornado-producing storm systems emit infrasound up to 2 hours before tornado genesis. This can be detected from large distances (in excess of 150 km) due to weak atmospheric attenuation at these frequencies. Thus, infrasound could be used for long-range, passive monitoring and detection of tornado genesis as well as characterisation of tornado properties.

5 Fire

Perhaps no other element better symbolises our current predicament than fire, as the burning of fossil fuels has been largely responsible for the rise in CO₂ emissions and the resulting temperature increase. Thus, fire in our work primarily stands for man-made climate change.
However, fire itself is also a consequence of man-made climate change. The world’s flora and fauna are under threat from the increased frequency and strength of forest fires. Tragically, those fires are now increasingly affecting residential areas, causing immense damage to communities. Therefore, we will additionally concern ourselves with the early detection of fire itself, where CA can also prove a valuable asset.

In this section, we will discuss the usefulness of CA in monitoring those aspects of human behaviour that are most detrimental to the environment.

5.1 Wildfires

Fires are primarily detected using either images or sensors for temperature, humidity, and smoke. While those measurements provide the de-facto standard for the detection of forest fires, they cannot readily distinguish between different types of fires. However, this differentiation is crucial in a world where wildfire seasons are getting longer and more intense, and fire brigades need to figure out how to best spread their limited resources. In that respect, crown fires, which burn through the upper layers of trees, are more intense and have a higher velocity than surface or ground fires. Distinguishing between these different types of fires is crucial for combating large wildfires, as it determines the type of response needed. While other modalities, such as imagery sensors, can be utilised for this categorisation, none of them is adequate on its own as each comes with its shortcomings: Cameras can be limited by smoke, while temperature, humidity, and smoke are best tailored to detect the presence of fire, but might be insensitive to its type. To that end, the acoustic properties of fires have been previously shown to vary across different types, thus, enabling their classification based on auditory perception [Khamukhin and Bertoldo 2016, Khamukhin et al. 2017]. Furthermore, microphone arrays can be used to determine the location of lightning thunder sources, since lightning strikes are one of the major causes of forest fires. This lays out a new promising direction for the timely classification of different forest fires which could provide crucial information for early combating them.

A further complicating factor is that fires will naturally disrupt any monitoring system put in place to detect them; e.g., as the fire itself, or the water used to extinguish it, destroys the sensors. Thus, immediately after the fire, affected areas will be left without sensory coverage. This constitutes a crucial challenge as the re-ignition of existing fires in already burnt-out areas is a major problem for firefighters. A poignant example is the August 2021 fire of Varympompi (near Athens, Greece[1]) which was initially controlled by the fire brigade, only to be re-ignited a few hours later due to insufficient supervision, with the majority of its destruction coming with the second wave. This illustrates that it is imperative to rapidly (re-)deploy sensing equipment in the affected areas. Those areas, however, will be heavily affected by smoke (especially if the fire is still ongoing in nearby land), thus, making it harder for image or smoke sensors to detect potential sources of rekindling. This necessitates the use of sensors whose effectiveness is not inhibited by the presence of fire and that is tailored to the classification of its type, rather than its detection only – another potential advantage of auditory perception over other modalities. However, domain adaptation is going to be a problem as the sound of fire will differ between forests.

5.2 Structures

Communities around the world struggle to reconvene their lives in the aftermath of a catastrophic fire, especially if the fire affected residential areas. One of the usual reaction to such fires is the promise to rebuild all destroyed or affected buildings. Unfortunately, building is one of a major source of CO₂ emissions, necessitating an environmentally-friendly rebuilding paradigm. This includes the effort to salvage as much as possible from the remnants of an urban fire.

A major consideration after a building fire is its effect on structural integrity, which is the ability of a structure to withstand the required load without collapsing. If this integrity is compromised to an irreparable extent, then the building needs to be demolished and reconstructed. Determining the extent of the damage, however, is not an easy feat, especially as any investigation needs to be conducted by means of non-invasive techniques that do not further

[1]https://go.ifrc.org/reports/14615
compromise a building’s integrity. This integrity is dependent on the change of strength of the materials a building is made from, which is in turn reflected by the way sound propagates; thus, CA presents a novel avenue of investigating changes in material strength which can provide useful information on the damage a building has sustained. As a recent example of such work, Schabowicz et al. [2019] study the condition of materials subjected to fire, and utilise acoustics for identifying the degree of degradation of fibre-cement boards.

5.3 Noise

From primitive people’s first use of fire to modern day industrial revolution, the shadow of fire can be felt with increasing frequency. Its presence is not only felt through visual or temperature stimuli, but through auditory stimuli as well. In particular, the latter are another byproduct of modern industry, with detrimental effects to human well-being and ecological equilibrium. Industry, machinery, and cities are the main sources of acoustic contamination. This has a major environmental impact and significant detrimental effects on wildlife [Halfwerk and Slabbekoorn 2015, Harding et al. 2019, Chan and Blumstein 2011], generating stress and jeopardising wildlife reproduction [Alquezar and Macedo 2019], potentially reducing biodiversity [Sordello et al. 2020], affecting wildlife communication strategies [Duquette et al. 2021], and even contributing to the outright extinction of some species [Templeton et al. 2016, Nabi et al. 2018]. With CA, abnormal noises can be monitored, identified, and dealt with in timely and decentralised fashion, as sensors can be spread across areas of interest. These could include wildlife habitats near industrial zones, motorways, airports, or railways; thus, zones where the presence of nature and mankind intersects.

The presence of noise pollution can be highly correlated to the presence of environmental pollution as well. For example, audio recordings can be used to determine the current volume of traffic in cities [Dekoninck et al. 2015]. This information can be used to determine current air pollution levels, so that countermeasures can be taken accordingly (e.g., directing traffic through alternative routes or issuing localised pollution warnings). Aside from such short-term measures, acoustic monitoring can be used for long-term mitigation as well. For example, monitoring of daily activity in modern megacities, in which significant transport results in a high degree of air pollution, can be used to inform public infrastructure projects. In addition, the emotional connotation of noise can be assessed automatically, providing the ability to monitor noise also in a qualitative rather than a sheer quantitative manner [Schuller et al. 2012].

5.4 Machines

When it comes to machine monitoring in a globalised and modern world in which machines play a very important role, computer acoustics can help in machine management, making sure that machines operate at optimal power consumption levels, or identifying ruptures. CA can assist in the timely identification of hazardous events and anomalous situations [Ntalampiras et al. 2010, 2009, 2011]. Recent advances on using microphones and audio recordings to avoid adverse conditions for tools and machinery have shown promise [Serin et al. 2020]. Problems can be solved by the utilisation of microphones in condition monitoring systems, which can be more beneficial than corrective maintenance since they allow early warnings of mechanical and electrical defects to prevent major component failures. For example, acoustic monitoring has been successfully applied for monitoring bearing and gearboxes by using acoustic sensors [Choudhary et al. 2019] and audio data collected by a cheap microphone has been utilised to monitor the condition of railway point machines [Lee et al. 2016].

Finally, there are several drawbacks to purely visual-based monitoring systems for industrial applications, such as occlusions by objects/smoke and illumination changes, to which audio-based detection systems would be more robust. In the study of Bayram et al. [2021], the proposed real-time acoustic anomaly detection system can be applied to recognise anomalous sound events such as fire, explosion, and glass breaking. This can be substantially improved by the use of CA to expand the sensor coverage area, improve sensor robustness (e.g., to low visibility conditions), and widen the scope of events that can be detected.
6 Aether

Aether is the name given to the fifth element introduced by Plato and Aristotle, what came to be considered the quintessence of things. It was an element that was considered discrete from the physical world, made of the air breathed by the Olympic gods. It thus properly fits as a stand-in for AI, whose nature is primarily ethereal, in the sense that it consists of an agglomeration of algorithms and ideas implemented as software.

Coming up with a proper definition for AI is a difficult task, especially as the field itself is rapidly and constantly changing. Perhaps the loosest of definitions is that it is a (computer) system which perceives and/or interacts with its environment in a way humans perceive as intelligent. In a more practical sense, it is a system with a mechanism for incorporating, and later utilising, knowledge. In recent years, knowledge acquisition has come to be dominated by the statistical learning paradigm [Vapnik, 1999], whose latest mainstay is deep learning [Goodfellow et al., 2016].

CA then is the sub-field of AI which concerns itself with auditory information. This includes all aspects of intelligence which utilise sound as a communication medium. The notion of communication is an important part of the definition, as communication theory is underpinned by the dual notions of sender and receiver. A CA system can function as both: it may perceive sounds already present in its environment or transmit its own sounds into it.

We note that ‘sound’ here is not defined purely by anthropomorphic criteria. While humans have come to define the gold standard as to what exactly constitutes intelligence, in the case of CA they are not the only, and perhaps not even the best, standard to measure up against. With our limited hearing, human auditory abilities are dwarfed by those of several animals [Wartzok and Ketten, 1999]. Accordingly, modern sound perception systems have already surpassed human capabilities, as the cases of hydrophones, ultrasound, and piezoelectric microphones demonstrate. Likewise, sound production systems have now progressed to a state far superior than the human speech production system, and are able to both generate a much wider range of sounds and broadcast them further away than any human could. Thus, we concern ourselves with sound as an umbrella term encompassing the propagation of vibrations over a diverse set of mediums.

However, capturing and transmitting sound is only the first step towards a cognitive CA agent. Understanding what is being heard, deciding what to transmit in response, and synthesising it are much harder problems. Sound generation, in particular for speech and music, has been revolutionised by WaveNet-derived architectures [Oord et al., 2016, Engel et al., 2017]. Intelligent audio analysis has been accordingly shaped by the advent of deep learning [Purwins et al., 2019]. The bridge between sound generation and sound analysis has remained under-researched, at least as far as machine-to-animal communication is concerned, but can draw advances from recent developments in dialogue systems [Chen et al., 2017] and reinforcement learning [Sutton and Barto, 2018], both of which can serve as building blocks for designing an interactive agent.

7 Audio Generation

So far we have only dealt with audio in context of sensing for a (distributed) intelligence system whose solitary purpose is to detect events of interest in the surrounding environment. However, an auditory communication channel can also be used for bidirectional communication between all entities connected to it. This enables us to equip our intelligent system with a transmission module as well, thus converting it from a passive sensing module to an agent capable of interacting with its environment. This section can be regarded as an excursus to examples where an intelligent generation of audio might be beneficial for nature.

7.1 Alarm Systems for Animals

Traditionally, the targeted receivers of machine communication have been human beings, as exemplified by the burgeoning field of human-computer interaction. This is also true in the context of emergency systems; fire alarms,
for instance, are used to notify humans to evacuate an area under threat. However, much of the negative effects of climate change are experienced by animals, not humans. For example, the 2019 wildfires in southeast Australia have endangered several species by killing millions of individual animals [Legge et al., 2020]. Yet, thankfully, those fires left behind far less human casualties (34) as residents were evacuated from surrounding areas in timely fashion. This indicates that part of those animal deaths could have been prevented if those animals had been appropriately evacuated as well. Unfortunately, tracking, let alone evacuating, wild animals on such vast expanses of nature is currently at the limit of our technical capabilities. Tracking has already been discussed in the previous sections. Now we will instead sketch a potential path towards a methodology suitable for animal evacuation.

The fundamental building block of such a system is machine-to-animal communication. Previous studies have established that certain animals use vocalisations to communicate with other member of their species, and in particular to alert them to the presence of threatening, or otherwise important, stimuli in their surrounding environment [Bradbury and Vehrencamp, 1998]. This existing mechanism could be appropriated by a distributed auditory intelligence to alert those animals, e.g., to the presence of a wildfire in their area. From a hardware consideration, this would only entail the introduction of speakers alongside microphones; a minor addition in terms of costs. From an AI perspective, this would require the transmission of appropriate vocalisations to be interpreted by the targeted animals as sounds of alarm, and correspondingly help them navigate the chaotic environment of a wildfire.

Generating those vocalisations is a challenging topic. The vocabulary of animal communication has largely not been decoded, yet; thus, to the best of our knowledge, there is no available solution to this problem. This is where the power of contemporary AI algorithms could come into play. Reinforcement learning has long been established as a learning paradigm for agents that actively interact with their environment. In this case, the generation of appropriate warning vocalisations could be recast as a reinforcement learning problem. The system generates sounds and monitors the reaction of the animals in its surroundings, which in turn acts as a reward until the target reaction is achieved.

At this point, it is worth mentioning that such a system would not only be limited to the wildfire use case. It can also be utilised for the protection of animals from other dangers, such as invasive hunter species or human poachers. After detecting potential dangers, appropriate vocalisations would be produced to warn the animals in threat and help them evacuate the area.

### 7.2 Open Space Active Noise Cancellation

Noise pollution is a major environmental hazard which can harm humans and animals alike (cf. section 5.3). The field which concerns itself with mitigating noise is noise cancellation, whereby measures are put in place to reduce, or even counteract, unwanted noise sources. Traditionally, this is handled by passive measures, such as by introducing noise barriers in motorways, which requires a rough estimation of the properties of the noise expected at a given area. In contrast, active noise cancellation (ANC) is based on an intentional transmission of a generated signal to destructively interfere with the noise that shall be cancelled. With the advent of more intelligent audio analysis modules, open space ANC could be largely improved in the coming years. In an ANC scenario, sensors and accompanying controllers are placed in several locations with the goal of identifying unwanted noise sources. In turn, they inform an actuator which produces an ‘anti-noise’ sound wave; essentially the same wave as the noise source but with an inverted phase [Lam et al., 2021]. Emphasis is therefore placed on the controller, which needs to decompose the input signal into its constituents so that the actuator can attempt to remove them, or at least reduce their unwanted side-effects. Although this application has a large upside, its applicability remains limited (so far), as synthesising a proper sound wave to counteract specific sources in open spaces is a very challenging problem [Srijomkwan et al., 2019]. Should a complete cancellation appear too challenging, there also exist approaches to enhance the present audio composition and improve certain characteristics such as tonality, harmonicity, or tempo to increase human [Baird et al., 2020] (and potentially animal or plant) wellbeing.
7.3 Sonification

Different kind of data, thus also non-audio data, can be converted into an audio representation and radiated in form of audible sound to convey information. For example, the sonification of human movement pattern is a common practice in contemporary performing arts [Landry and Jeon, 2020], but can be also utilised as a feedback technique in physiotherapeutic treatment [Guerra et al., 2020]. Besides, data sonification can be a useful technique for applications in favour of nature and environment as well. In an exhibit at the National Center for Atmospheric Research, Boulder, Colorado, USA, climate data are presented as sounds in order to sensibilise visitors for global climate processes and to make them better understand the ongoing climate change. This innovative installation called “Sounding Climate” is based on data from the Community Earth System Model Large Ensemble Project and allows people to auditorily explore changes in temperature, precipitation, or sea ice over time since 1920 [Gardiner et al., 2018]. A better understanding of ongoing climate processes might have a positive influence on people’s attitude on our nature and their future interaction with our planet. Another project highlighting the potential of data sonification to raise people’s awareness about unsustainable use of valuable natural resources, such as short water supplies, is the composition of “The Lament of Las Tablas de Daimiel” [Angeler et al., 2018]. This song builds upon a 71-year time series of rainfall and inundation area data and expresses the disruption of wetland in Spain due to agricultural transformation by means of a soprano and a bass voice. Intelligent sonification modules, e.g., based on reinforcement learning techniques, could automatically identify, where and when people should get exposed to sounds generated from originally non-audible nature-related processes and which sounds/instruments should be used for specific settings and individuals to gain the maximum effect for the benefit of our planet.

8 Discussion

The plenty of identified, already existing use cases of CA and audio generation in the context of environmental and climate-related questions, demonstrates the potential of this so far rather disregarded methodology to help saving our planet. Admittedly, most presented approaches do no directly contribute to ‘save the planet’, but ‘just’ to monitor nature or nature-related processes in the first place. However, monitoring of natural phenomena and early detection of changes or suboptimal environmental conditions represents an important requirement for any, audio- and non-audio-related, active technology-based intervention or initiation of human action. The presented overview shows that we are steering the right course by being open-minded for novel approaches at a time where our planet needs urgent help. However, what are the advantages of CA over alternative approaches? What are its limitations? Are there considerations from an ethics perspective? Is CA already set to reasonably contribute? In the remainder of this work, we aim to give answers to these questions.

8.1 Computer Audition vs Alternatives

There are several ways to capture environmental and climate-related processes on our planet with audio recording being just one example suited for intelligent/machine learning-based analysis. Visual sensing is another example of established data collection for computer-based analysis, i.e., computer vision. In addition, various other sensing alternatives, e.g., other physical or chemical sensors, exist that are and might be used to gather input data for intelligent environment and climate monitoring and harm detection systems. Further, these sensors can be compared with the non-technology-based possibilities of the human body.

Table 1 compares these different modalities with audio in terms of data throughput, covered area, privacy, information richness, availability of ML models as well as costs and the degree to which they pollute the environment.
Table 1: Comparison of acoustic sensing for environment and climate change monitoring vs other sensing modalities with regard to seven key criteria. Overall grading: +/green shading = advantageous, +-/orange shading = neutral, -/red shading = disadvantageous; m = meter(s); ML = machine learning

| Criteria | Acoustic | Visual | Other physical | Chemical | Human |
|----------|----------|--------|----------------|----------|-------|
| Data throughput | + Extent of audio data is modest most of the time | + 2D images tend to be petite, while 3D images or videos tend to be comparatively large | + Data stream is manageable in size | + Data stream is manageable in size | + Sensing continuously; however, cannot really be transmitted from one human to another or to a computer |
| Covered area | + Several hundred to several thousand m² (e.g., thunder); 360° recording angle possible (omnidirectional microphone) | + Variable dependent on specific camera type; especially high range for aerial/satellite cameras; limited angle of view | + Very focused on one location; sometimes representative for a bigger area, e.g., temperature | -/red shading = disadvantageous | + Depends on the modality (vision, touch, etc.); can be large but also quite limited |
| Privacy | + Critical in case human voice is recorded [Kröger et al., 2019]; not applicable for most scenarios in context of climate change | + Critical in case human faces are recorded [Jose et al., 2019]; not applicable for most scenarios in context of climate change | + Not critical | + Critical blood or saliva analysis, or genetic sequencing not applicable in context of nature | + Unproblematic as no human data are recorded at all |
| Info richness | + Many sound sources possible within one audio recording (e.g., animal sounds, rain, cars) | + Many objects, classes, locations can be captured in one photo or video | + Mostly built to sense specific information, i.e., only the desired information is recorded | + Mostly built to sense specific information, i.e., only the desired information is recorded | + Due to synchronous multimodal sensing of the human body, lots of information is captured and processed in the brain |
| ML models | + Many pretrained models available, which use raw audio or acoustic features as input | + Many pretrained models available, which use raw video or visual features as input | + A few available models [Hansen et al., 2021] [Wang et al., 2020] [Vanseekrishna et al., 2020] | - Very few to none existent models with respect to climate | - No models available |
| Costs | + Microphones are generally cheap, even specialised microphones are not too expensive | -/red shading = disadvantageous | + Mostly relatively cheap | + Sensor materials/resources can be expensive, i.e., sensor costs vary a lot | + The human body needs no further sensors; auxiliary means such as glasses are not too expensive |
| Pollution | + Each sensor pollutes the environment to some degree; can be reused very often | + Shooting satellites into orbit emits lots of burnt gas and precipitates debris [Ross and Vedda, 2018] [Adilov et al., 2015] | + Each sensor pollutes the environment to some degree; can be reused quite often | + Each sensor pollutes the environment to some degree; can be reused only sometimes | + Presumably the most environment-friendly option |
8.2 Generalisation

One of the major critiques of machine learning systems is their (lack of) ability to generalise. This is most poignantly exemplified by their susceptibility to adversarial attacks [Szegedy et al., 2014] – minor perturbations to their inputs that lead to vastly different predictions. While substantial research has been devoted to understand and mitigate this phenomenon, it is far from a solved problem, thus limiting the applicability of models in real world settings. Moreover, according to the standard machine learning paradigm, the deployment environment must be identical to the training one; a constraint that is currently impossible to satisfy without vastly increasing the amount of data that is available for training. This need is overcome via domain adaptation algorithms [Ben-David et al., 2006], which explicitly minimise the discrepancy between source and target domains.

Moreover, the issue of generalisation is further complicated by the recently introduced notion of underspecification of machine learning architectures [D’Amour et al., 2020], which also impacts auditory models [Triantafyllopoulos et al., 2021]. Underspecification corresponds to the inability to predict the behaviour of a machine learning model in its deployment environment based on its behaviour in its training environment. It constitutes a major challenge for real world applications as it makes model selection and, more crucially, model testing harder, leading to catastrophic failures during deployment. This is of particular importance for a large-scale deployment required for environmental monitoring, where a model will have to perform equally well across several different locations, and, correspondingly, needs to be addressed via further research.

For audio analysis in particular, the notion of generalisation is closely linked to that of robustness to different perturbations, a topic that has received considerable attention over the years. Traditionally, robustness has been studied under the auspices of speech enhancement [Wang and Chen, 2018, Rethage et al., 2018, Liu et al., 2021, Triantafyllopoulos et al., 2019], where (human) speech constitutes the signal of interest and (environmental) noise the unwanted interference that needs to be removed. However, in our case the opposite would be true – human voices would need to be removed in order to get more robust measurements of the environmental conditions [Liu et al., 2020].

Overall, generalisation is still the primary concern, especially when the information procured by the deployed models will lead to decisions with important ramifications for the environment and our future.

8.3 Efficiency

Data is the fuel that drives contemporary AI applications. Bigger and better data usually leads to bigger and better models, which require (vastly) more computational power to be trained [Schwartz et al., 2020]. This trend places a significant, and ever increasing, strain on the world’s resources [Strubell et al., 2019b]; a potentially flagrant oversight when creating models that attempt to reduce that strain. Moreover, inconsiderate pursuit for more (sources of) data can potentially compromise privacy and democracy [Yu, 2016, Helbing et al., 2019], both pillars of the social cohesion necessary to tackle climate change.

It is thus imperative to seek more resource efficient approaches for AI in general and CA in particular. This includes the ability to learn from less data. Two prominent learning paradigms that may be of use here are those of transfer learning [Pan and Yang, 2009] and zero-shot learning [Wang et al., 2019, Xie and Virtanen, 2021]: the former corresponds to transferring knowledge from other tasks, usually ones for which data is abundant; the latter to generalising to classes unseen during training. However, while both these paradigms have been successfully utilised in several applications, further work is needed to understand in more detail how they work and streamline their application [Neyshabur et al., 2020, Triantafyllopoulos and Schuller, 2021].

A key obstacle to the incorporation of more complex machine intelligence technology, such as deep learning-based solutions, into production-ready CA applications, is the significant amount of resources (e.g., computational power) required for data collection, model training, and inference [Strubell et al., 2019a]. As a result, a movement on sustainable AI is being promoted among the research community. Sustainable AI can be understood as having two branches: AI...
for sustainability and sustainability of AI. The former one focuses on using AI towards the sustainable development goal[2] and the latter aims at the reduction of carbon emissions and computing power used in AI methodology itself [Wynsberge 2021]. The whole research community is slowly but steadily detouring towards changing the entire lifecycle of AI products (i.e., idea generation, training, and implementation) to achieve greater ecological integrity. It is focusing its efforts on different alternatives, such as the use of flexible and lightweight data augmentation, which can be incorporated into training processes to boost performance and robustness, saving training resources and improving generalisation of models. Besides cross-corpus learning, cross-modal transfer learning techniques can be used to leverage knowledge from pre-trained neural networks based on state-of-the-art architectures across different domains. Furthermore, novel technologies for resource optimisation, such as low-parameter architectures [Amiriparian et al., 2021], leveraging compression techniques [Cheng et al., 2018], pruning, or teacher student networks, are being further developed to reduce the computational footprint of AI. Sustainable AI is about developing AI that is compatible with sustaining environmental resources for current and future generations, while keeping in mind that there are environmental costs to AI itself.

8.4 Trustability

While AI is often touted as a technology capable of operating completely autonomously, the truth is that most AI applications are embedded in an ecosystem involving other entities, primarily humans. This introduces the additional requirement of trustability: The entities that interact with an AI program must trust the program under consideration of known limitations, in order to take its outputs and decisions properly into account. For humans, trustability is largely related to explainability [Ignatiev 2020], a concept that remains elusive [Lipton 2018] but on which significant progress has nevertheless been made [Adadi and Berrada 2018]. Explainability corresponds to the ability of an AI agent to explain its decisions, that is, break its causes down to easily digestible attributions. Interestingly, in our application scenario, it is possible to imagine other entities coming in contact with AI models; in particular, animals (cf. section 7.1). Consequently, these entities should also be taken into account when attempting to endow any CA systems with notions of explainability and trustability. While this may seem as an exotic field of study (that to our knowledge remains unresearched), it may prove crucial for saving the world’s biodiversity.

8.5 Bias

All real-world AI technologies are plagued by bias. Audition in particular is affected, as sources of signal are difficult to determine and can come from a wide range of generative factors. The typical AI setup involves sampling from the real world, creating a dataset, and training a model to perform a task in this sampled space. Through identifying spurious correlations and bias from study design sampling methods, AI models are often able to perform well in these sampled datasets. This wrongly suggests a true underlying signal and so opportunity for AI to help in a field. This has been demonstrated in the recent COVID-19 pandemic, where early research suggested COVID-19 was uniquely identifiable from infected individuals’ respiratory sounds [Coppock et al., 2021]. Moving forward, CA for the environment should be directed down biologically plausible avenues and significant work should be done on study design and bias mitigation.

8.6 Ethical Considerations

Over the years, several different guidelines have been proposed, each encompassing a different set of principles for ethical AI [Jobin et al., 2019, Hagendorff 2020, Quadrianto et al., 2021], including such tailored for specific audio [Batliner et al., 2020], all of which are relevant for CA systems put in use against climate change. We highlight two of the most pertinent ones below, namely fairness and privacy, and refer the interested reader to recent overviews of ethical AI for a more general discussion.

---

[2]https://sdgs.un.org/es/goals
Fairness is one important consideration for the ethical application of AI. It is necessary to provide adequate performance guarantees for all parts of our planet’s ecosystem, irrespective of where in the world those may be [Triantafyllopoulos et al., 2021]. This becomes particularly pressing as the areas of the world that are most in danger tend to be more strained for resources. It is thus easy to imagine a scenario where the richest countries collect most of the data within their borders, leading to an underrepresentation of the world’s more vulnerable countries in the training, and, consequently, to the underperformance of the algorithms when deployed on their premises.

Privacy is another big risk in the era of big data [Yu, 2016]. This regards the possibility of mass surveillance, especially in applications such as environmental monitoring, where the large-scale deployment of several sensors is mandated. Such a widespread deployment of sensors, in our case microphones, puts in danger citizens around the world whose data might be stored, shared, and analysed without their knowledge or permission. Protecting that privacy is possible under several different paradigms. Perhaps the most straightforward one is to remove all speech information immediately after capture and before any subsequent processing is done [Liu et al., 2020]; this strategy, however, might lead to suboptimal results as any source separation algorithm invariably introduces unwanted artefacts and information loss. Alternatively, the federated learning paradigm could be followed, where the data is processed only at edge nodes and that information is then streamed in order to train a global model while preserving the privacy of those nodes [Li et al., 2020]. Federated learning has been successfully applied in many areas, such as healthcare [Xu et al., 2021], sensing in smart cities [Jiang et al., 2020], and financial services [Shingi, 2020, Long et al., 2020]. However, there are core challenges of federated learning [Li et al., 2020]. For instance, this paradigm is not completely privacy-proof [Bonawitz et al., 2017] and may also lead to worse performance [Bonawitz et al., 2017, McMahan et al., 2018]. Altogether, privacy remains a largely unsolved problem for AI systems operating on data that may include personal information. Nevertheless, for many of the applications outlined here, this is not a primary concern, as they focus on wildlife monitoring.

Finally, we want to point out that the typical formulation of ethical dilemmas in AI is highly anthropocentric, thus, concentrating primarily on the effect of AI on human affairs, and, even in the cases where it touches upon its ecological aspects, it does so from the human perspective as well. This anthropocentric view has been challenged by several scholars arguing for the development of environmental or ecological ethics [Brennan and Lo, 2002, Curry, 2011].

At this point, we have to generally recap that the ultimate aim of this work was to give a current overview of applications where CA (and intelligent audio generation) technology might contribute to ‘save our planet’. Thus, we need to shed light on the essential question of what does saving our planet actually mean. Strictly speaking, saving our planet implies that the Earth is preserved as long as possible, with or without a human population. Nevertheless, some applications outlined in this work seem to be beneficial for human individuals at first glance rather than for the planet itself, such as the early detection of a tornado. However, in this work, we regard the basic need of mankind to further populate the Earth as its habitat as given and, under these circumstances, the prevention of human beings from physical harm or material damage might prevent costly and pollutive medical interventions or the resources-consuming replacement of goods. Thereby, we followed the dominant paradigm, putting humanity and its interests in the centre of discussion, but we acknowledge the need for a holistic consideration of our natural ecosystem.

8.7 Outlook

CA is already used in a variety of applications in the context of environmental and climate change-related issues. Compared to other alternatives, CA has several advantages, such as providing cost-effective coverage of large areas and enabling early detection of changes even before they become apparent in other modalities. Therefore, CA seems to be on the right track and definitely has the potential to impact future applications. However, more work needs to be done to exploit the full potential of audio intelligence in this area. In particular, it is important to overcome some methodological limitations, while always respecting the ethical framework by, e.g., ensuring privacy and fairness of the models. In order to further increase the power of audio intelligence applications, a combination of CA with other
techniques would be worth striving for in the future, leading to intelligent multimodal sensing applications, e. g., in the form of computer audio-vision based systems.

With this work we would like to convince researchers of the potential of audio intelligence in combating climate change and hope that many will follow our call-to-action to continue what has already been initiated and explore new applications of CA and intelligent audio generation in the various fields related to environmental and climate issues in order to jointly contribute to the preservation of our habitat and to saving our planet.

Our planet is crying for help. Let us use Computer Audition to hear those cries and translate them to action!

Acknowledgements

This work was funded by the German Research Foundation (DFG; Reinhart Koselleck project, No. 442218748: AUDIONOMOUS). The authors want to thank everyone who takes responsibility for our beautiful planet and makes an effort to prevent nature from harm. Zero GPU hours were consumed to provide the contents discussed herein.

Conflict of Interest Statement

The author Björn W. Schuller was employed by the company audEERING GmbH. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

Jordan T. Abell, Gisela Winckler, Robert F. Anderson, and Timothy D. Herbert. Poleward and weakened westerlies during Pliocene warmth. *Nature*, 589:70–75, 2021.

Amina Adadi and Mohammed Berrada. Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE Access*, 6:52138–52160, 2018.

Nodir Adilov, Peter J Alexander, and Brendan M Cunningham. An economic analysis of earth orbit pollution. *Environmental and Resource Economics*, 60(1):81–98, 2015.

Juan Jose Alava, Peter S Ross, Cara Lachmuth, John KB Ford, Brendan E Hickie, and Frank APC Gobas. Habitat-based PCB environmental quality criteria for the protection of endangered killer whales (orcinus orca). *Environmental Science & Technology*, 46(22):12655–12663, 2012.

Renata D. Alquezar and Regina H. Macedo. Airport noise and wildlife conservation: What are we missing? *Perspectives in Ecology and Conservation*, 17(4):163–171, 2019.

Shahin Amiriparian, Tobias Hübner, Maurice Gerczuk, Sandra Ottl, and Björn W. Schuller. DeepSpectrumLite: A power-efficient transfer learning framework for embedded speech and audio processing from decentralised data. *arXiv preprint arXiv:2104.11629*, 2021.

Nagaraju Andavarapu and Valli Kumari Vatsavayi. Wild-animal recognition in agriculture farms using W-COHOG for agro-security. *International Journal of Computational Intelligence Research*, 13(9):2247–2257, 2017.

David G Angeler, Miguel Alvarez-Cobelas, and Salvador Sánchez-Carrillo. Sonifying social-ecological change. *Ecology and Society*, 23(2), 2018.

Nicholas John Ashbolt. Microbial contamination of drinking water and disease outcomes in developing regions. *Toxicology*, 198(1-3):229–238, 2004.

Muthuraj Ashokan, Ganesan Latha, Ayadura Thirunavukkarasu, Govindan Raguraman, and Ramasamy Venkatesan. Iceberg cracking events as identified from underwater ambient noise measurements in the shallow waters of Ny-Alesund, Arctic. *Polar Science*, 10(2):140–146, 2016.
Alice Baird, Meishu Song, and Björn W. Schuller. Interaction with the soundscape – exploring an emotional audio generation approach for improved individual wellbeing. In *Proceedings of the Artificial Intelligence in HCI International Conference (AI-HCI)*, volume 12217 of *Lecture Notes in Computer Science*, pages 229–242, Copenhagen, Denmark, 2020. Springer.

Sandra Banholzer, James Kossin, and Simon Donner. The impact of climate change on natural disasters. In *Reducing disaster: Early warning systems for climate change*, pages 21–49. Springer, 2014.

Rolf Bardeli, Daniel Wolff, Frank Kurth, Martina Koch, Klaus H. Tauchert, and Karl-Heinz Frommolt. Detecting bird sounds in a complex acoustic environment and application to bioacoustic monitoring. *Pattern Recognition Letters*, 31(12):1524–1534, 2010.

Anton Batliner, Simone Hantke, and Björn Schuller. Ethics and good practice in computational paralinguistics. *IEEE Transactions on Affective Computing*, 11, 2020.

Barış Bayram, Taha Berkay Duman, and Gökhan Ince. Real time detection of acoustic anomalies in industrial processes using sequential autoencoders. *Expert Systems*, 38(1):e12564, 2021.

Shai Ben-David, John Blitzer, Koby Crammer, Fernando Pereira, et al. Analysis of representations for domain adaptation. *Proceedings of the International Conference on Neural Information Processing Systems (NeurIPS)*, 19:137–144, 2006.

Christian Bergler, Hendrik Schröter, Rachael Xi Cheng, Volker Barth, Michael Weber, Elmar Nöth, Heribert Hofer, and Andreas Maier. ORCA-SPOT: An automatic killer whale sound detection toolkit using deep learning. *Scientific Reports*, 9(1):1–17, 2019.

Daniel T. Blumstein, Daniel J. Mennill, Patrick Clemins, Lewis Girod, Kung Yao, Gail Patricelli, Jill L. Deppe, Alan H. Krakauer, Christopher Clark, Kathryn A. Cortopassi, et al. Acoustic monitoring in terrestrial environments using microphone arrays: applications, technological considerations and prospectus. *Journal of Applied Ecology*, 48(3):758–767, 2011.

Keith Bonawitz, Vladimir Ivanov, Ben Kreuter, Antonio Marcedone, H. Brendan McMahan, Sarvar Patel, Daniel Ramage, Aaron Segal, and Karn Seth. Practical secure aggregation for privacy-preserving machine learning. In *Proceedings of the ACM SIGSAC Conference on Computer and Communications Security*, pages 1175–1191, Dallas, USA, 2017. ACM.

Jack W. Bradbury and Sandra L. Vehrencamp. Principles of animal communication. 1998.

Andrew Brennan and Norva Lo. Environmental ethics. *Stanford Encyclopedia of Philosophy*, 2002.

Gerardo Ceballos, Paul R. Ehrlich, and Rodolfo Dirzo. Biological annihilation via the ongoing sixth mass extinction signaled by vertebrate population losses and declines. *Proceedings of the National Academy of Sciences*, 114(30):6089–6096, 2017.

Alvin Aaden Yim-Hol Chan and Daniel T. Blumstein. Attention, noise, and implications for wildlife conservation and management. *Applied Animal Behaviour Science*, 131(1):1–7, 2011.

Hongshen Chen, Xiaorui Liu, Dawei Yin, and Jiliang Tang. A survey on dialogue systems: Recent advances and new frontiers. *Acm Sigkdd Explorations*, 19(2):25–35, 2017.

Yu Cheng, Duo Wang, Pan Zhou, and Tao Zhang. Model compression and acceleration for deep neural networks: The principles, progress, and challenges. *IEEE Signal Processing Magazine*, 35(1):126–136, 2018.

Baptiste Chide, Naomi Murdoch, Yannick Bury, Sylvestre Maurice, Xavier Jacob, Jonathan P. Merrison, Jens J. Iversen, Pierre-Yves Meslin, Marti Bassas-Portús, Alexandre Cadu, Anthony Sournac, Bruno Dubois, Ralph D. Lorenz, David Mimoun, and Roger C. Wiens. Experimental wind characterization with the supercam microphone under a simulated martian atmosphere. *Icarus*, 354:114060–114072, 2021.
Anurag Choudhary, Deepam Goyal, Sudha Letha Shimi, and Aparna Akula. Condition monitoring and fault diagnosis of induction motors: A review. *Archives of Computational Methods in Engineering*, 26:1221–1238, 2019.

Christopher W Clark and James H Johnson. The sounds of the bowhead whale, *balaena mysticetus*, during the spring migrations of 1979 and 1980. *Canadian Journal of Zoology*, 62(7):1436–1441, 1984.

Reginald B. Cocroft and Rafael L. Rodriguez. The behavioral ecology of insect vibrational communication. *BioScience*, 55(4):323–334, 04 2005.

Harry Coppack, Lyn Jones, Ivan Kiskin, and Björn W. Schuller. Covid-19 detection from audio: Seven grains of salt. *The Lancet Digital Health*, 3(9):537–538, 2021.

Josh Cowls, Andreas Tsamados, Mariarosaria Taddeo, and Luciano Floridi. The AI Gambit—Leveraging artificial intelligence to combat climate change: Opportunities, challenges, and recommendations. *AI & Society*, pages 1–25, 2021.

WC Cummings and DV Holliday. Sounds and source levels from bowhead whales off pt. barrow, alaska. *The Journal of the Acoustical Society of America*, 82(3):814–821, 1987.

Patrick Curry. *Ecological ethics: An introduction*. Polity, 2011.

Valerie A Curtis. Dirt, disgust and disease: a natural history of hygiene. *Journal of Epidemiology & Community Health*, 61(8):660–664, 2007.

Chunli Dai, Bretwood Higman, Patrick J Lynett, Mylène Jacquemart, Ian M Howat, Anna K Liljedahl, Anja Dufresne, Jeffrey T Freymueller, Marten Geertsema, Melissa Ward Jones, et al. Detection and assessment of a large and potentially tsunamigenic periglacial landslide in barry arm, alaska. *Geophysical Research Letters*, 47(22), 2020.

Alexander D’Amour, Katherine Heller, Dan Moldovan, Ben Adlam, Babak Alipanahi, Alex Beutel, Christina Chen, Jonathan Deaton, Jacob Eisenstein, Matthew D Hoffman, et al. Underspecification presents challenges for credibility in modern machine learning. *arXiv preprint arXiv:2011.03395*, 2020.

Grant B Deane, Oskar Glowacki, M. Dale Stokes, and Erin C. Pettit. The underwater sounds of glaciers. *Acoustics Today*, 15(4):12–19, 2019.

Luc Dekoninck, Dick Botteldooren, and Luc Int Panis. Sound sensor network based assessment of traffic, noise, and air pollution. In *Proceedings of the European Congress and Exposition on Noise Control Engineering (Euronoise)*, pages 2321–2326, Maastricht, The Netherlands, 2015.

Cameron Albert Duquette, Scott R. Loss, and Torre J. Hovick. A meta-analysis of the influence of anthropogenic noise on terrestrial wildlife communication strategies. *Journal of Applied Ecology*, 58(6):1112–1121, 2021.

Brian R. Elbing and Christopher Petrin. Monitoring infrasound from a tornado in oklahoma. *The Journal of the Acoustical Society of America*, 143(3):1808–1808, 2018.

Jesse Engel, Cinjon Resnick, Adam Roberts, Sander Dieleman, Mohammad Norouzi, Douglas Eck, and Karen Simonyan. Neural audio synthesis of musical notes with wavenet autoencoders. In *Proceedings of the International Conference on Machine Learning (ICML)*, pages 1068–1077, Sydney, Australia, 2017. PMLR.

Almo Farina, Maria Ceraulo, Christopher Bobryk, Nadia Pieretti, Enza Quinci, and Emanuele Lattanzi. Spatial and temporal variation of bird dawn chorus and successive acoustic morning activity in a mediterranean landscape. *Bioacoustics*, 24, 09 2015.

José D Figueroa, Timothy Fout, Sean Plasynski, Howard McIlvried, and Rameshwar D Srivastava. Advances in co2 capture technology—the us department of energy’s carbon sequestration program. *International Journal of Greenhouse Gas Control*, 2(1):9–20, 2008.

Lauren A Freeman, Joan A Kleypas, and Arthur J Miller. Coral reef habitat response to climate change scenarios. *PloS one*, 8(12):e82404, 2013.
Monica Gagliano, Stefano Mancuso, and Daniel Robert. Towards understanding plant bioacoustics. *Trends in Plant Science*, 17:323–325, 03 2012.

Lisa S Gardiner, Clara Deser, Marty Quinn, Becca Hatheway, Sharon Clark, Tim Scheitlin, Matt Rehme, and Adam Phillips. Sounding climate: An exhibit showcasing data sonification and visualization from the community earth system model. In *AGU Fall Meeting Abstracts*, Washington D.C., USA, 2018.

Michael Garstang and Michael C Kelley. Understanding animal detection of precursor earthquake sounds. *Animals*, 7 (9):66, 2017.

Rory Gibb, Ella Browning, Paul Glover-Kapfer, and Kate E Jones. Emerging opportunities and challenges for passive acoustics in ecological assessment and monitoring. *Methods in Ecology and Evolution*, 10(2):169–185, 2019.

Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.

Timothy Gordon, Andrew Radford, Isla Davidson, Kasey Barnes, Kieran Mcloskey, Sophie Nedelec, Mark Meekan, Mark Mccormick, and Stephen Simpson. Acoustic enrichment can enhance fish community development on degraded coral reef habitat. *Nature Communications*, 10(1):1–7, 2019.

Joao Guerra, Lee Smith, Domenico Vicinanza, Brendon Stubbs, Nicola Veronese, and G Williams. The use of sonification for physiotherapy in human movement tasks: A scoping review. *Science & Sports*, 35(3):119–129, 2020.

Carolyn-Monika Görres and David Chesmore. Active sound production of scarab beetle larvae opens up new possibilities for species-specific pest monitoring in soils. *Scientific Reports*, 9:10115, 07 2019.

Thilo Hagendorff. The ethics of AI ethics: An evaluation of guidelines. *Minds and Machines*, 30(1):99–120, 2020.

Wouter Halfwerk and Hans Slabbekoorn. Pollution going multimodal: the complex impact of the human-altered sensory environment on animal perception and performance. *Biology Letters*, 11(4):20141051, 2015.

Stéphane Hallegatte. *Natural disasters and climate change*. Springer, 2016.

Marwah Sattar Hanoon, Ali Najah Ahmed, Nur’atiah Zaini, Arif Razzaq, Pavitra Kumar, Mohsen Sherif, Ahmed Sefelnasr, and Ahmed El-Shafie. Developing machine learning algorithms for meteorological temperature and humidity forecasting at terengganu state in malaysia. *Scientific Reports*, 11(1):1–19, 2021.

James E Hansen and Makiko Sato. Paleoclimate implications for human-made climate change. In *Climate change*, pages 21–47. Springer, 2012.

Simone Hantke, Nicholas Cummins, and Björn Schuller. What is my dog trying to tell me? The automatic recognition of the context and perceived emotion of dog barks. In *Proceedings of the International Conference on Acoustics, Speech, and Signal Processing, (ICASSP)*, pages 5134–5138, Calgary, Canada, 2018. IEEE.

Harry R Harding, Timothy AC Gordon, Emma Eastcott, Stephen D Simpson, and Andrew N Radford. Causes and consequences of intraspecific variation in animal responses to anthropogenic noise. *Behavioral Ecology*, 30: 1501–1511, 2019.

Nail Hasan and Motasim Badri. Effect of ambient temperature on dawn chorus of house sparrows. *Environment & Ecology Research*, 4:161–168, 05 2016.

Dirk Helbing, Bruno S Frey, Gerd Gigerenzer, Ernst Hafen, Michael Hagner, Yvonne Hofstetter, Jeroen Van Den Hoven, Roberto V Zicari, and Andrej Zwitter. Will democracy survive big data and artificial intelligence? In *Towards Digital Enlightenment*, pages 73–98. Springer, 2019.

Bretwood Higman, Dan H Shugar, Colin P Stark, Göran Ekström, Michele N Koppes, Patrick Lynett, Anja Dufresne, Peter J Haeussler, Marten Geertsema, Sean Gulick, et al. The 2015 landslide and tsunami in Taan Fiord, Alaska. *Scientific Reports*, 8(1):1–12, 2018.

Ove Hoegh-Guldberg and John F Bruno. The impact of climate change on the world’s marine ecosystems. *Science*, 328 (5985):1523–1528, 2010.
Alexey Ignatiev. Towards trustable explainable ai. In Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI), pages 5154–5158, Yokohama, Japan, 2020.

North American Bird Conservation Initiative. The State of the Birds United States of America 2009. U.S. Department of Interior, 2009.

Ji Chu Jiang, Burak Kantarci, Sema Oktug, and Tolga Soyata. Federated learning in smart city sensing: Challenges and opportunities. Sensors, 20(21), 2020.

Anna Jobin, Marcello Ienca, and Efpy Vayena. The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9):389–399, 2019.

Edwin Jose, M Greeshma, Mithun TP Haridas, and MH Supriya. Face recognition based surveillance system using FaceNet and MTCNN on Jetson TX2. In Proceedings of the International Conference on Advanced Computing & Communication Systems (ICACCS), pages 608–613, Coimbatore, India, 2019. IEEE.

Jacob Kamminga, Eyuel Ayele, Nirvana Meratnia, and Paul Havinga. Poaching detection technologies—a survey. Sensors, 18(5):1474, 2018.

I. Khait, R. Sharon, R. Perelman, A. Boonman, Y. Yovel, and L. Hadany. Plants emit remotely detectable ultrasounds that can reveal plant stress. bioRxiv, 2019.

Aleksandr Anatolievich Khamukhin, Anton Yurievich Demin, Dmitriy Mikhailovich Sonkin, S Bertoldo, G Perona, and V Kretova. An algorithm of the wildfire classification by its acoustic emission spectrum using wireless sensor networks. 803(1):012067, 2017.

Alexander A Khamukhin and Silvano Bertoldo. Spectral analysis of forest fire noise for early detection using wireless sensor networks. In Proceedings of the international Siberian conference on control and communications (SIBCON), pages 1–4, Kazan, Russia, 2016. IEEE.

Sookyung Kim, Hyojin Kim, Joonseok Lee, Sangwoong Yoon, Samira Ebrahim Kahou, Karthik Kashinath, and Mr Prabhat. Deep-hurricane-tracker: Tracking and forecasting extreme climate events. In Proceedings of the Winter Conference on Applications of Computer Vision (WACV), pages 1761–1769, Waikoloa Village, Hawaii, 2019. IEEE.

Holger Klinck, Sharon L Nieukirk, David K Mellinger, Karolin Klinck, Haruyoshi Matsumoto, and Robert P Dziak. Seasonal presence of cetaceans and ambient noise levels in polar waters of the north atlantic. The Journal of the Acoustical Society of America, 132(3):EL176–EL181, 2012.

Nancy Knowlton. The future of coral reefs. Proceedings of the National Academy of Sciences, 98(10):5419–5425, 2001.

Bernie Krause and Almo Farina. Using ecoacoustic methods to survey the impacts of climate change on biodiversity. Biological Conservation, 195:245–254, 2016.

Jacob Leon Kröger, Otto Hans-Martin Lutz, and Philip Raschke. Privacy implications of voice and speech analysis—information disclosure by inference. In IFIP International Summer School on Privacy and Identity Management, pages 242–258, Windisch, Switzerland, 2019. Springer.

Andreas König. Extending bee hive health state monitoring by integrated acoustical sensing and machine learning. In Proceedings of the International Conference on Sensors and Electronic Instrumentation Advances (SEIA), pages 168–173, Corfu, Greece, 2019.

Bhan Lam, Woon-Seng Gan, DongYuan Shi, Masaharu Nishimura, and Stephen Elliott. Ten questions concerning active noise control in the built environment. Building and Environment, 200:107928, 2021.

Timothy Lamont, Ben Williams, Lucille Chapuis, Mochyudho Prasetya, Marie Seraphim, Harry Harding, Eleanor May, Noel Janetski, Jamaluddin Jompa, David Smith, Andrew Radford, and Stephen Simpson. The sound of recovery: Coral reef restoration success is detectable in the soundscape. Journal of Applied Ecology, 12 2021.
Steven Landry and Myounghoon Jeon. Interactive sonification strategies for the motion and emotion of dance performances. *Journal on Multimodal User Interfaces*, 14(2):167–186, 2020.

Jonguk Lee, Heesu Choi, Dahee Park, Yongwha Chung, Hee-Young Kim, and Sukhan Yoon. Fault detection and diagnosis of railway point machines by sound analysis. *Sensors*, 16(549):1–12, 2016.

Kevin M Lee, Preston S Wilson, and Erin C Petitit. Underwater sound radiated by bubbles released by melting glacier ice. 20(1):070004, 2013.

Sarah Legge, John Woinarski, Stephen Garnett, Dale Nimmo, Ben Scheele, Mark Lintermans, Nicki Mitchell, Nick Whiterod, and Jason Ferris. Rapid analysis of impacts of the 2019–20 fires on animal species, and prioritisation of species for management response. *Report prepared for the Wildlife and Threatened Species Bushfire Recovery Expert Panel*, 14:120–121, 2020.

Chiara Lepore, Ryan Abernathey, Naomi Henderson, John T. Allen, and Michael K. Tippett. Future global convective environments in CMIP6 models. *Earth’s Future*, 9(12):1–21, 2021.

Tian Li, Anit Kumar Sahu, Ameet Talwalkar, and Virginia Smith. Federated learning: Challenges, methods, and future directions. *IEEE Signal Processing Magazine*, 37(3):50–60, 2020.

Tzu-Hao Lin, Tomonari Akamatsu, Frederic Sinniger, and Saki Harii. Exploring coral reef biodiversity via underwater soundscapes. *Biological Conservation*, 253:108901, 2021.

Zachary C Lipton. The mythos of model interpretability: In machine learning, the concept of interpretability is both important and slippery. *Queue*, 16(3):31–57, 2018.

Shuo Liu, Andreas Triantafyllopoulos, Zhao Ren, and Björn W. Schuller. Towards speech robustness for acoustic scene classification. In *Proceedings of the Annual Conference of the International Speech Communication Association (INTERSPEECH)*, Shanghai, China, 2020. ISCA.

Shuo Liu, Gil Keren, and Björn W. Schuller. N-hans: Introducing the augsburg neuro-holistic audio-enhancement system. *Multimedia Tools & Applications*, 80:28365–28389, 2021.

Yunjie Liu, Evan Racah, Joaquin Correa, Amir Khosrowshahi, David Lavers, Kenneth Kunkel, Michael Wehner, William Collins, et al. Application of deep convolutional neural networks for detecting extreme weather in climate datasets. *arXiv preprint arXiv:1605.01156*, 2016.

Guodong Long, Yue Tan, Jing Jiang, and Chengqi Zhang. Federated learning for open banking. pages 240–254, 2020.

Alex E. Lumsdon, Ivan Artamonov, Maria Cristina Bruno, Maurizio Righetti, Klement Tockner, Diego Tonolla, and Christiane Zarfl. Soundpeaking–hydropeaking induced changes in river soundscapes. *River Research and Applications*, 34(1):3–12, 2018.

Richard W. Mankin, David W. Hagstrum, Mark T. Smith, Amy Roda, and Moses T. K. Kairo. Perspective and promise: a century of insect acoustic detection and monitoring. *American Entomologist*, 57:30–44, 2011.

Richard W. Mankin, Daniel Stanaland, Muhammad Haseeb, Barukh Rohde, Octavio Menocal, and Daniel Carrillo. Assessment of plant structural characteristics, health, and ecology using bioacoustic tools. *Proceedings of Meetings on Acoustics*, 33(1):010003, 2018.

Duncan D. Mara. Water, sanitation and hygiene for the health of developing nations. *Public Health*, 117(6):452–456, 2003.

Aleksey V. Marchenko, Eugene G. Morozov, and Sergey V. Muzylev. A tsunami wave recorded near a glacier front. *Natural Hazards and Earth System Sciences*, 12(2):415–419, 2012.

Vincent Martin, Véronique Chevalier, Pietro Ceccato, Assaf Anyamba, Lorenzo De Simone, Juan Lubroth, Stéphane De La Rocque, and Joseph Domenech. The impact of climate change on the epidemiology and control of Rift Valley fever. *Revue Scientifique et Technique de l’Office International des Épizooties*, 27(2):413–426, 2008.
Valérie Masson-Delmotte, Panmao Zhai, Anna Pirani, Sarah L Connors, Clotilde Péan, Sophie Berger, Nada Caud, Yang Chen, Leah Goldfarb, Melissa I Gomis, et al. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, 2021.

Gagan Matta and Avinash Kumar. Health risk, water hygiene, science and communication. ESSENCE-International Journal for Environmental Rehabilitation and Conservation, 1:179–186, 2017.

H Brendan McMahan, Daniel Ramage, Kunal Talwar, and Li Zhang. Learning differentially private recurrent language models. In Proceedings of the International Conference on Learning Representations (ICLR), Vancouver, Canada, 2018.

Fatemehsadat Mireshghallah, Mohammadkazem Taram, Praneeth Vepakomma, Abhishek Singh, Ramesh Raskar, and Hadi Esmaeilzadeh. Privacy in deep learning: A survey. arXiv preprint arXiv:2004.12254, pages 1–24, 2020.

Sandra Müller, Martin M Gossner, Caterina Penone, Kirsten Jung, Swen C Renner, Almo Farina, Lisa Anhäuser, Manfred Ayasse, Steffen Boch, Falk Haensel, et al. Land-use intensity and landscape structure drive the acoustic composition of grasslands. Agriculture, Ecosystems & Environment, 328:107845, 2022.

Tobias M Müller, Eva Caspari, Qiaomu Qi, J Germán Rubino, Danilo Velis, Sofia Lopes, Maxim Lebedev, and Boris Gurevich. Acoustics of partially saturated rocks: Theory and experiments. In Seismic Exploration of Hydrocarbons in Heterogeneous Reservoirs: New Theories, Methods and Applications, pages 45–75. Elsevier, 2015.

Steven Ness and George Tzanetakis. Human and machine annotation in the Archive, a large scale bioacoustic archive. In Proceedings of the Global Conference on Signal and Information Processing (GlobalSIP), pages 1136–1140, Atlanta, USA, 2014. IEEE.

Steven Ness, Helena Symonds, Paul Spong, and George Tzanetakis. The Archive: Data mining a massive bioacoustic archive. arXiv preprint arXiv:1307.0589, 2013.

Behnam Neyshabur, Hanie Sedghi, and Chiyuan Zhang. What is being transferred in transfer learning? In Proceedings of the International Conference on Neural Information Processing Systems (NeurIPS), online, 2020.

Stavros Ntalampiras, Ilyas Potamitis, and Nikos Fakotakis. An adaptive framework for acoustic monitoring of potential hazards. EURASIP Journal on Audio, Speech, and Music Processing, 2009:1–15, 10 2009.

Stavros Ntalampiras, Ilyas Potamitis, and Nikos Fakotakis. A multidomain approach for automatic home environmental sound classification. In Proceedings of the Annual Conference of the International Speech Communication Association (INTERSPEECH), pages 2210–2213, Chiba, Japan, 2010. ISCA.

Stavros Ntalampiras, Ilyas Potamitis, and Nikos Fakotakis. Probabilistic novelty detection for acoustic surveillance under real-world conditions. Transactions on Multimedia, 13(4):713–719, 2011.

Aaron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, and Koray Kavukcuoglu. Wavenet: A generative model for raw audio. pages 125–140, 2016.

Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22(10):1345–1359, 2009.

NL Panwar, SC Kaushik, and Surendra Kothari. Role of renewable energy sources in environmental protection: A review. Renewable and Sustainable Energy Reviews, 15(3):1513–1524, 2011.

James Riddick Partington. A short history of chemistry. Courier Corporation, 1989.

Vidushi Patel, Natasha Pauli, Eloise Biggs, Liz Barbour, and Bryan Boruff. Why bees are critical for achieving sustainable development. Ambio, 50, 04 2020.
Supa Pengpid and Karl Peltzer. Hygiene behaviour and health attitudes in african countries. *Current Opinion in Psychiatry*, 25(2):149–154, 2012.

Rajeev Pillay, Robert J. Fletcher Jr, Kathryn E. Sieving, Bradley J. Udell, and Henry Bernard. Bioacoustic monitoring reveals shifts in breeding songbird populations and singing behaviour with selective logging in tropical forests. *Journal of Applied Ecology*, 56(11):2482–2492, 2019.

Daniel Plazas-Jiménez and Marcus V. Cianciaruso. Valuing ecosystem services can help to save seabirds. *Trends in Ecology & Evolution*, 35(9):757–762, 2020.

Alexandre Ponomarenko, Olivier Vincent, Amoury Pietriga, Hervé Cochard, É Badel, and Philippe Marmottant. Ultrasonic emissions reveal individual cavitation bubbles in water-stressed wood. *Journal of the Royal Society Interface*, 11(99):20140480, 2014.

Barry M Popkin, Kristen E D’Anci, and Irwin H Rosenberg. Water, hydration, and health. *Nutrition Reviews*, 68(8):439–458, 2010.

Deepa S Pureswaran, Alain Roques, and Andrea Battisti. Forest insects and climate change. *Current Forestry Reports*, 4(2):35–50, 2018.

Hendrik Purwins, Bo Li, Tuomas Virtanen, Jan Schlüter, Shuo-Yiin Chang, and Tara Sainath. Deep learning for audio signal processing. *IEEE Journal of Selected Topics in Signal Processing*, 13(2):206–219, 2019.

Novi Quadrianto, Björn W. Schuller, and Finnian Rachel Lattimore. Editorial: Ethical machine learning and artificial intelligence. *Frontiers in Big Data and Frontiers in Artificial Intelligence, section Machine Learning and Artificial Intelligence, Special Issue on Ethical Machine Learning and Artificial Intelligence*, 4(742589):1–3, 08 2021.

Clionadh Raleigh and Henrik Urdal. Climate change, environmental degradation and armed conflict. *Political Geography*, 26(6):674–694, 2007.

Björn Rethage, Jordi Pons, and Xavier Serra. A wavenet for speech denoising. In *Proceedings of the International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 5069–5073, Calgary, Canada, 2018. IEEE.

Patrick Ritz and Gilles Berrut. The importance of good hydration for day-to-day health. *Nutrition Reviews*, 63:S6–S13, 2005.

Martin Ross and James A Vedda. The policy and science of rocket emissions. *Center for Space Policy and Strategy, The Aerospace Corporation*, pages 2–10, 2018.

Y Samuel, SJ Morreale, CW Clark, CH Greene, and ME Richmond. Underwater, low-frequency noise in a coastal sea turtle habitat. *The Journal of the Acoustical Society of America*, 117(3):1465–1472, 2005.

Krzysztof Schabowicz, Tomasz Gorzelanicyk, and Mateusz Szymków. Identification of the degree of degradation of fibre-cement boards exposed to fire by means of the acoustic emission method and artificial neural networks. *Materials*, 12(4):656–674, 2019.

Quirin Schiermeier. Huge landslide triggered rare greenland mega-tsunami. *Nature News*, pages 1–4, 2017.

Björn Schuller, Simone Hantke, Felix Weninger, Wenjing Han, Zixing Zhang, and Shrikanth Narayanan. Automatic recognition of emotion evoked by general sound events. In *Proceedings of the International Conference on Acoustics, Speech, and Signal Processing, (ICASSP)*, pages 341–344, Kyoto, Japan, 03 2012. IEEE.

Björn W. Schuller, Anton Batliner, Christian Bergler, Florian Pokorny, Jarek Krajewski, Meg Cychosz, Ralf Vollmann, Sonja-Dana Roelen, Sebastian Schnieder, Erika Bergelson, Alejandrina Cristià, Amanda Seidl, Lisa Yankowitz, Elmar Nöth, Shahin Amiriparian, Simone Hantke, and Maximilian Schmitt. The interspeech 2019 computational paralinguistics challenge: Styrian dialects, continuous sleepiness, baby sounds & orca activity. In *Proceedings of the Annual Conference of the International Speech Communication Association (INTERSPEECH)*, pages 2378–2382, Graz, Austria, 2019. ISCA.
Björn W. Schuller, Anton Batliner, Christian Bergler, Cecilia Mascolo, Jing Han, Iulia Lefter, Heysem Kaya, Shahin Amiriparian, Alice Baird, Lukas Stappen, et al. The interspeech 2021 computational paralinguistics challenge: Covid-19 cough, covid-19 speech, escalation & primates. arXiv preprint arXiv:2102.13468, pages 1–5, 2021.

Roy Schwartz, Jesse Dodge, Noah A Smith, and Oren Etzioni. Green AI. Communications of the ACM, 63(12):54–63, 2020.

Çağan H. Şekercioğlu, Gretchen C. Daily, and Paul R. Ehrlich. Ecosystem consequences of bird declines. 101(52):18042–18047, 2004.

Çağan H Şekercioğlu, Richard B Primack, and Janice Wormworth. The effects of climate change on tropical birds. Biological Conservation, 148(1):1–18, 2012.

James Robert Self and RM Wasikom. Nitrates in drinking water. PhD thesis, Colorado State University. Libraries, 1992.

Gokberk Serin, Benhür Sener, A. Murat Ozbayoglu, and Hakki Ozgur Unver. Review of tool condition monitoring in machining and opportunities for deep learning. International Journal of Advanced Manufacturing Technology, 109:953–974, 2020.

Geet Shingi. A federated learning based approach for loan defaults prediction. In Proceedings of the International Conference on Data Mining Workshops (ICDMW), pages 362–368, Sorrento, Italy, 2020.

Lorna M Slade and Baraka Kalangahe. Dynamite fishing in tanzania. Marine Pollution Bulletin, 101(2):491–496, 2015.

Romain Sordello, Ophélie Ratel, Frédérique Flamerie De Lachapelle, Clément Léger, Alexis Dambry, and Sylvie Vanpeene. Evidence of the impact of noise pollution on biodiversity: a systematic map. Environmental Evidence, 9:1–27, 2020.

K Srijomkwan, C Weerasakul, S Kittiwearawong, and J Puntree. The cancellation of human sounds using synthesized soundwaves. Journal of Physics: Conference Series, 1380(1):1–6, 2019.

Dan Stowell, Michael D. Wood, Hanna Pamula, Yannis Stylianou, and Hervé Glotin. Automatic acoustic detection of birds through deep learning: The first bird audio detection challenge. Methods in Ecology and Evolution, 10(3):368–380, 2019.

Emma Strubell, Ananya Ganesh, and Andrew McCallum. Energy and policy considerations for deep learning in NLP. CoRR, abs/1906.02243:1–6, 2019a.

Emma Strubell, Ananya Ganesh, and Andrew McCallum. Energy and policy considerations for deep learning in NLP. In Proceedings of the Annual Meeting of the Association for Computational Linguistics, pages 3645–3650, Florence, Italy, 2019b.

Richard S Sutton and Andrew G Barto. Reinforcement learning: An introduction. MIT press, 2018.

Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. In Proceedings of the International Conference on Learning Representations (ICLR), Banff, Canada, 2014.

Christopher N. Templeton, Sue Anne Zollinger, and Henrik Brumm. Traffic noise drowns out great tit alarm calls. Current Biology, 26(22):R1173–R1174, 2016.

Diego Tonolla, Mark S Lorang, Kurt Heutschi, and Klement Tockner. A flume experiment to examine underwater sound generation by flowing water. Aquatic Sciences, 71(4):449–462, 2009.

Andreas Triantafyllopoulos and Björn W. Schuller. The role of task and acoustic similarity in audio transfer learning: Insights from the speech emotion recognition case. In Proceedings of the International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 7268–7272, 2021.

Andreas Triantafyllopoulos, Gil Keren, Johannes Wagner, Ingmar Steiner, and Björn W. Schuller. Towards robust speech emotion recognition using deep residual networks for speech enhancement. In Proceedings of the Annual
Andreas Triantafyllopoulos, Manuel Milling, Konstantinos Drossos, and Björn W. Schuller. Fairness and underspecification in acoustic scene classification: The case for disaggregated evaluations. In Proceedings of the Detection and Classification of Acoustic Scenes and Events Workshop (DCASE), online, 2021.

Joseph Turian, Jordie Shier, Humair Raj Khan, Bhiksha Raj, Björn W. Schuller, Christian J. Steinmetz, Colin Malloy, George Tzanetakis, Gissel Velarde, Kirk McNally, Max Henry, Nicolas Pinto, Camille Noufi, Christian Clough, Dorien Herremans, Eduardo Fonseca, Jesse Engel, Justin Salamon, Philippe Esling, Pranay Manocha, Shinji Watanabe, Zeyu Jin, and Yonatan Bisk. Hear 2021: Holistic evaluation of audio representations. arXiv preprint arXiv:, 2022.

RJ Urick. The noise of melting icebergs. The Journal of the Acoustical Society of America, 50(1B):337–341, 1971.

A Vanseekrishna, R Nishitha, T Anil Kumar, K Hanuman, and Ch G Supriya. Prediction of temperature and humidity using IoT and machine learning algorithm. In Proceedings of the International Conference on Intelligent and Smart Computing in Data Analytics (ISCDA), pages 271–279, Andhra Pradesh, India, 2020. Springer.

Vladimir Vapnik. The nature of statistical learning theory. Springer Science & Business Media, 1999.

DeLiang Wang and Jitong Chen. Supervised speech separation based on deep learning: An overview. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 26(10):1702–1726, 2018.

Rui Wang, Karthik Kashinath, Mustafa Mustafa, Adrian Albert, and Rose Yu. Towards physics-informed deep learning for turbulent flow prediction. In Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 1457–1466, online, 2020. ACM.

Wei Wang, Vincent W Zheng, Han Yu, and Chunyan Miao. A survey of zero-shot learning: Settings, methods, and applications. ACM Transactions on Intelligent Systems and Technology (TIST), 10(2):1–37, 2019.

Douglas Wartzok and Darlene R Ketten. Marine mammal sensory systems. Biology of Marine Mammals, 1:117–175, 1999.

Nick Watts, W Neil Adger, Paolo Agnolucci, Jason Blackstock, Peter Byass, Wenjia Cai, Sarah Chaytor, Tim Colbourn, Mat Collins, Adam Cooper, et al. Health and climate change: policy responses to protect public health. The Lancet, 386(10006):1861–1914, 2015.

Sue Wells. Dynamite fishing in northern tanzania–pervasive, problematic and yet preventable. Marine Pollution Bulletin, 58(1):20–23, 2009.

Tim Wheeler and Jochim Von Braun. Climate change impacts on global food security. Science, 341(6145):508–513, 2013.

Christopher Whelan, Dan Wenny, and Robert Marquis. Ecosystem services provided by birds. Annals of the New York Academy of Sciences, 1134:25–60, 07 2008.

Aimee Wynsbergh. Sustainable ai: Ai for sustainability and the sustainability of ai. AI and Ethics, 1:1–6, 02 2021.

Huang Xie and Tuomas Virtanen. Zero-shot audio classification via semantic embeddings. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 29:1233–1242, 2021.

Jie Xu, Benjamin S Glicksberg, Chang Su, Peter Walker, Jiang Bian, and Fei Wang. Federated learning for healthcare informatics. Journal of Healthcare Informatics Research, 5(1):1–19, 2021.

Shui Yu. Big privacy: Challenges and opportunities of privacy study in the age of big data. IEEE Access, 4:2751–2763, 2016.