International Journal of Biometeorology (2021) 65:779–803
https://doi.org/10.1007/s00484-020-02063-z

REVIEW PAPER

# Technological opportunities for sensing of the health effects of weather and climate change: a state-of-the-art-review

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Received: 8 July 2020 / Revised: 23 November 2020 / Accepted: 10 December 2020 / Published online: 11 January 2021
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## Abstract

Sensing and measuring meteorological and physiological parameters of humans, animals, and plants are necessary to understand the complex interactions that occur between atmospheric processes and the health of the living organisms. Advanced sensing technologies have provided both meteorological and biological data across increasingly vast spatial, spectral, temporal, and thematic scales. Information and communication technologies have reduced barriers to data dissemination, enabling the circulation of information across different jurisdictions and disciplines. Due to the advancement and rapid dissemination of these technologies, a review of the opportunities for sensing the health effects of weather and climate change is necessary. This paper provides such an overview by focusing on existing and emerging technologies and their opportunities and challenges for studying the health effects of weather and climate change on humans, animals, and plants.

**Keywords** Biometeorology · Environmental sensing · Human · Animal and plant health · Measurement technologies

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## Introduction

Technological advancements have greatly facilitated data acquisition across disciplines, leading to innovations in the cross-disciplinary field of biometeorology. This field of science focuses on the interactions between the biosphere (i.e., all living organisms, including plants, animals, and humans) and the Earth's atmosphere in space and time (Tromp 1980; McGregor 2012; Gosling et al. 2014). The diverse field of biometeorology allows for the collaboration of many disciplines including, but not limited to, meteorology, geography, biology, mathematics and statistics, environmental science, animal welfare and behavior, urban climatology, epidemiology, public health, and physiology.

Measuring and sensing contribute to our understanding of climatological, biological, and physiological processes. This can inform and optimize climate change mitigation and adaptation. For example, rising temperatures have been found to have an adverse impact on human, animal, and plant health (Cavicchioli et al. 2019; Harwatt 2019). In this respect, data acquisition is a key component of studying and understanding the complex interactions that occur between atmospheric processes and the health of the living world. As such, biometeorology is reliant on the sensing and measurement of these physiological parameters. Newly designed sensing technologies have provided both meteorological and biological data across increasingly vast spatial, spectral, and temporal scales, and further across unprecedented thematic scales. Addressing the cross-sectoral impacts of weather and climate change requires an "un-siloed" and multi-disciplinary approach. Furthermore, information and communication technologies have dramatically reduced barriers to data dissemination enabling the circulation of information across countries and disciplines faster and more reliably than ever.

Researchers and practitioners alike benefit from the use of a wide array of measurement technologies to advance research, especially on the health effects of weather and climate change. Due to the rapid growth and advancement of sensing technologies, a comprehensive review of the opportunities for sensing the health effects of weather and climate change is necessary. Thus, the goal of this paper is to present the state of scientific development of existing and emerging sensing technologies used in biometeorological studies, building upon a recent short communication by Mehdipoor et al. (2017). To this end, we provide an overview of existing and emerging technologies that are used or have the potential for use in understanding the health effects of weather and climate change on humans, animals, and plants. Furthermore, we review challenges that may be encountered in the use and deployment of these technologies. Current and emerging technologies are introduced and organized by scale and their direct relevance for study of human, animal, and plant biometeorology. Finally, sensing parameters and approaches used across these scales are presented for addressing novel challenges in the study of human, animal, and plant health in relation to weather and climate change.

## Systematic review

A systemic review was undertaken to identify relevant literature on biometeorological sensing technologies. Multiple search engines were used in this review including Google Scholar, Web of Science, Scopus, Scholars Portal, ProQuest, and the University of Twente and University of Toronto digital databases. The search keywords were grouped into themes as presented in Table 1.

Recent advances and newly developed techniques in biometeorological monitoring were prioritized over conventional or historical technologies. A total of 2395 items were located through database searches as shown in Fig. 1. This was complemented by a review of conference papers, books, and publications from various governmental and international organizations. A total of 267 studies were included as part of this review paper.

## Scale of sensing technologies

Interactions between the atmosphere and biosphere are bidirectional with the mechanisms that alter atmospheric processes to human, animal, and plant health issues occurring at different scales in space and time (Hungate and Koch 2015; Suni et al. 2015). Understanding the influence of scale on the dynamics of the atmosphere—biosphere system is fundamental to the selection of technologies and methods for undertaking biometeorological measurements. New and emerging technologies offer opportunities for undertaking biometeorological studies at various scales. Pulido Barrera et al. 2018used qualitative spatial classes (i.e., individual, local, regional, and global) to conceptualize metabolic processes for organisms, populations, ecosystems, and landscapes in urban areas. Generic quantitative approaches have been defined highlighting the spatial and temporal scale of biological processes (Munns 2002; Jorgensen and Nielsen 2013; Suni et al. 2015). As with biological processes, atmospheric processes are ordered across space and time (Oke 2008), yet both processes are so often illustrated in separate space-time diagrams. Figure 2 shows the relationship between these two conceptual views, with space representing the main medium of coincidence of both processes.

Sensing and measurement technologies have different temporal scales of measurement and are dependent on the spatial scale. For human and animal vitals, the temporal scale can be seconds or less. For microscale weather data, measurements are taken by the minute to the hour. Other sensing

**Table 1** Keywords and search terms

| Themes | Search terms |
|---|---|
| General | Biometeorology and low-and middle-income countries (LMIC) |
| | Technology and biometeorology and Africa |
| Citizen science | (Crowd sourcing or citizen science) and climate |
| | (Crowd sourcing or citizen science) and urban climate |
| | Volunteered phenological information |
| Environmental sensing networks | Netatmo |
| | Wunderground |
| | Internet of things and Urban climate |
| | Internet of Things weather sensors |
| | Wireless sensor networks |
| | Measuring solar radiation |
| | Low cost sensors to measure solar radiation |
| | Soil moisture measurement sensors |
| | Urban climate network |
| | Urban meteorological network |
| | Outdoor Thermal Comfort and Wearable* |
| | Passive air samplers |
| | (Air or water or soil) quality monitoring |
| | (Carbon dioxide or ozone or nitrogen dioxide) monitoring |
| | Air quality and (sampling or forestry or green roofs or green walls or agroforestry or green space or green infrastructure) |
| | Environment monitoring: biological levels of organization |
| | Remote sensing |
| | High-resolution satellite remote sensing |
| | Landsat |
| | MODIS |
| | MethaneSAT and RapidEye |
| Sensing network - Plants | (IoT or Internet of Things) and plant monitoring |
| | (Multispectral sensing or hyperspectral sensing) of plants |
| | Reflectance sensing of plant canopy |
| | UV spectroscopy of plants |
| | Nanosensors and plant monitoring |
| | Nanosensors and (smart farming or smart agriculture) |
| | Nanosensors and plant health |
| | Ranspiration rate sap flow sensors |
| Thermal comfort in humans | (Climate or Environment) and thermoregulation |
| | (Climate or Environment) and physiology |
| | (Climate or Environment) and stress |
| | Temperature and (stress or physiology or thermoregulation) |
| | Microclimate or micro-climate and (assessment or measurement) |
| | Mean Radiant temperature and health |
| | Biometeorological survey |
| | Heat and Health and Sensing and urban |
| | Urban climate |
| | Urban bioclimate |
| | Outdoor thermal comfort and (health or microscale or local or global) |
| | Human biometeorology |
| | Urban heat island |
| | Surface urban heat island |

**Table 1** (continued)

| Themes | Search terms |
|---|---|
| | Heatwaves |
| | Heat exposure |
| | Extreme temperatures and mortality |
| | Thermal sensing of human |
| | Digitally invisible population |
| Thermal comfort in animals | Thermal equilibrium and mammals and livestock |
| | Indirect calorimetry and heat production and gas exchanges rates and livestock and mammals |
| | Thermal physiology and livestock and mammals |
| | Thermal plasticity and free-living animals |
| | Biologging and free-ranging animals |
| | Thermal sensing of animals |
| Data visualization | Visualization and review and climate |
| | Visualization and climate |

technologies such as satellite monitoring and their derived products are less granular, ranging from every 15 min to hourly and monthly outputs. Table 2 summarizes different examples of technologies and sensors related to physiological processes, environmental conditions, and behavioral factors of humans, animals, and plants for various spatial scales. This table includes both traditional meteorological scales including micro-, meso-, and macro-scales according to Oke (2007), as well as individual-scale technologies. It also illustrates whether the technology can be used for animal, plant, and/or human applications. It should be noted that there is an unequal distribution of technological advancements across the three main fields of biometeorology, with a greater emphasis on human applications.

## Individual and micro-scale sensing

Microscale technology has the potential to enable the smart monitoring of plants, soils, and environmental conditions required to implement a new generation of precision agriculture practices that will further optimize agricultural production and reduce costs and environmental impacts (Stafford 2000; Shang et al. 2019). Moreover, these sensors can be used to create Internet of Things (IoT) networks for various

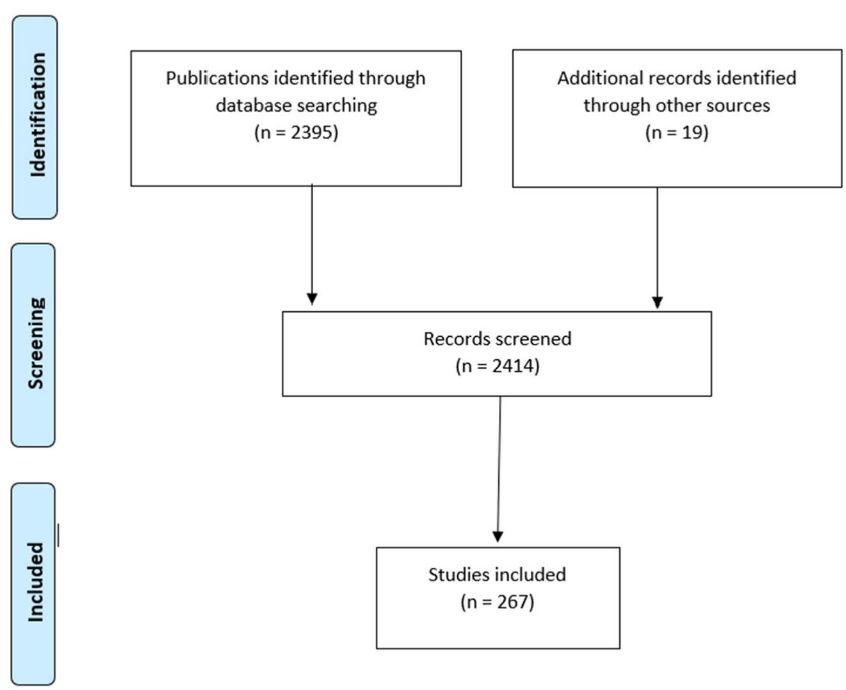


**Fig. 1** Overview of studies identified in the steps of the systematic review process derived from the PRISMA flow diagram (source: Moher et al. 2009)

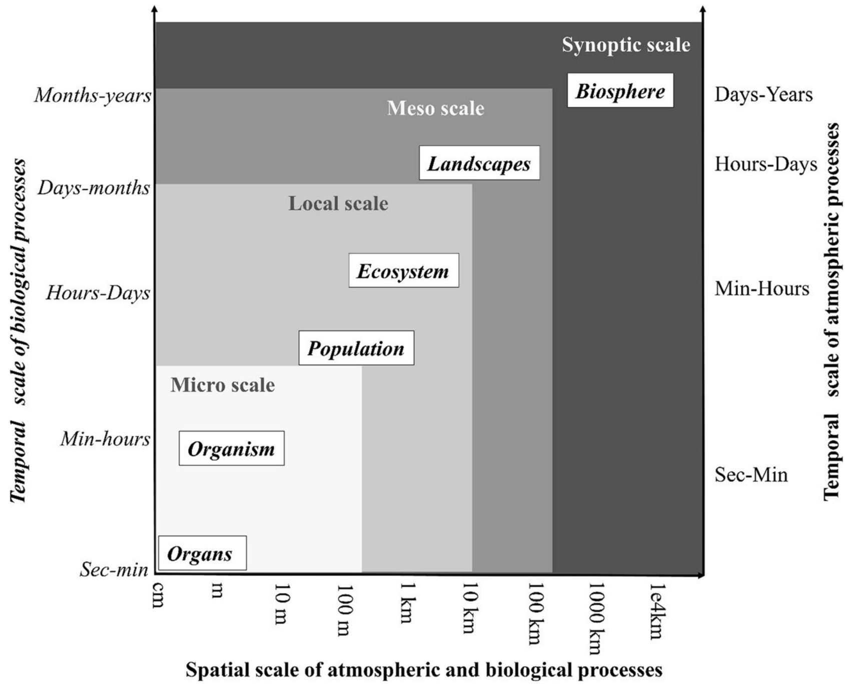


**Fig. 2** Spatial and temporal diagram illustrating the occurrence of both biological processes (levels of biological organization) and atmospheric processes (climatic scales)

applications, for instance, to measure environmental conditions such as relative humidity (Ganeshkumar et al. 2016), or to detect diseases such as bacterial leaf spot on peppers and tomatoes (Kwak et al. 2017). In terms of animal biometeorology, microchip technologies can be used to evaluate the effect of weather variation on sperm motility in livestock (de Wagenaar et al. 2016). In addition, smart sensors such as microneedles, skin patches, skin tattoos, and stretchable electronics can be used for physiological sensing with regard to meteorological and climatological conditions (Hosu et al. 2019), such as sweat rate through galvanic skin response, sodium levels in sweat, skin temperature, and heart rate (Kim and Rogers 2008; Harbert et al. 2013; Fan et al. 2014).

At the individual scale, wearable, implantation, or ingestible monitors and sensors (Dougherty et al. 2009; Gill and Sleivert 2001; Kuras et al. 2017) are commonly used in biometeorology to measure vital human parameters in both controlled experiments and daily life. Common vital signs measured include heart rate, respiratory rate, blood pressure, body temperature, cardiac rhythm, skin perspiration, and blood oxygen saturation (Lee et al. 2009; Taniguchi et al. 2011; Wakabayashi et al. 2011; Dias and Paulo Silva Cunha 2018). In addition, wearable devices are used to measure microclimate conditions and individual human exposure to weather. These include iButtons, Kestrel Drops, and UV dosimeters that collect data on body and air temperature, humidity, and UV radiation (Dias and Paulo Silva Cunha 2018; Hass and Ellis 2019). Accuracy of personal heat exposure measurement devices is in a range of ± 0.2–0.5 or ± 2.5–8% (Kuras et al. 2017). Another way to assess the effect of weather on individual health is through analyzing changes in body chemistry by sampling blood and saliva (Celec et al. 2009; Kanikowska et al. 2010). For example, cytokine levels in the blood will rise during heat stroke (Leon and Helwig 2010). In addition, portable saliva tests are a novel way to test for dehydration caused by heat and activity (Lu et al. 2019).

Studies to evaluate the thermal status of animals and the dynamics of gas exchanges can be undertaken using simple indirect calorimetry setups with facial masks, hoods, or heat exchangers to determine metabolic heat production, sensible and latent heat transfer, plus enteric methane emissions of ruminants (e.g., broilers chickens, Nascimento et al. 2017; dairy cows and beef cattle, de Melo Costa et al. 2018). For large animal species, particularly bovines, equids, and camelids, this is a novel technological development as it removes the need to (a) individually confine animals within climate chambers and (b) further removes the need for highly specialized equipment generally required by direct and indirect calorimetry studies. This provides opportunities to simultaneously collect data from larger cohorts of animals and enables institutions without access to climate chambers to conduct this type of research.

There are greater challenges in the assessment of physiological and behavioral responses in free-ranging wild species compared to the less complex livestock environment such as large grazing pastures or open confinement areas. In the wilderness context, animals are less predictable, and evaluations are performed in much larger territorial areas where animal restraint can be a significant challenge. Biologging approaches can be used to assess aspects of autonomic and behavioral thermoregulation in free-ranging animals on a large temporal scale (Fuller et al. 2014). For ecological purposes,

**Table 2** Spatial scales and examples of related biometeorological research topics (adapted from Oke 2006 and Muller et al. 2013)

| Spatial scale | Area extent | Applications | Example technologies | Usage (A, animals; P, plants; H, humans) |
|---|---|---|---|---|
| Individual scale | individual organism | Physiological processes, environmental conditions, and behavioral factors of humans, animals, and plants | Monitoring environmental stress on plants with nano-sensors (Shang et al. 2019). | P |
| | | | Use of lab on a chip technology (de Wagenaar et al. 2016; van der Helm et al. 2016; Hentschel et al. 2020) | A, H |
| | | | Ingestible devices such as smart pills (Koziolek et al. 2019; Morán-Navarro et al. 2019); tags coupled to accelerometer to monitor animal behavior (Wolfger et al. 2015) | A, H |
| | | | Wearable health devices, sensors, and/or thermal cameras (Lee et al. 2009; Taniguchi et al. 2011; Wakabayashi et al. 2011; Dias and Paulo Silva Cunha 2018; Liu et al. 2019; Aryal and Becerik-Gerber 2019) | A, H |
| | | | Microclimate conditions and individual human exposure to weather, e.g., iButtons, Kestrel Drops, and UV meters collect data on air temperature, humidity, and UV radiation (Dias and Paulo Silva Cunha 2018; Hass and Ellis 2019; Runkle et al. 2019)Kuras et al. 2017; Kuras et al. 2015) | H |
| | | | Subjective feedback surveys for indoor thermal, noise, and acoustic comfort using smart-watch and/or smartphone (Intille et al. 2016; Jayathissa et al. 2019; Jayathissa et al. 2020; Sood et al. 2019; Sood et al. 2020) | H |
| | | | Changes in body chemistry by taking and analyzing blood and saliva samples (Celec et al. 2009; Kanikowska et al. 2010) | A, H |
| | | | Indirect calorimetry studies to determine thermal equilibrium (metabolic heat production, sensible and latent heat transfer of animals) and to measure physiological responses (Camerro et al. 2016; de Melo Costa et al. 2018; Nascimento et al. 2019) | A |
| | | | Thermochron iButtons for the assessment of Individually experienced temperatures (IETs) (Kuras et al. 2015; Runkle et al. 2019) | H |
| Micro-scale | $\leq 10^2$ m | Outdoor heat/cold stress, thermal comfort | Mobile, custom-built human biometeorological platforms that measure air temperature, relative humidity, wind speed, and/or longwave and shortwave radiant flux densities (Höppe 1992; Ali-Toudert and Mayer 2007; Kenny et al. 2017; Middel and Krayenhoff 2019; Seo et al. 2019) | A, P, H |
| | | | Fixed measurements of short-wave and long-wave radiation simultaneously from six directions (east, west, north, south, upward and downward) (Thorsson et al. 2007; Johansson et al. 2014) or from two directions at a time by pyranometers and pyrgeometers ((VDI 3787 2008; Kántor et al. 2016) | H |
| | | | Portable micrometeorological thermal comfort set by AHLBORN (Lehnert et al. 2020) or Kestrel (Aminipouri et al. 2019; Xu et al. 2019a) | H |
| | | | Mobile Urban Microclimatic Monitoring (MUMiM) - open-source and low-cost meteorological device (Mauree et al. 2019) | H |
| | | | Weather stations and/or heat stress meters (Thorsson et al. 2007; Klok et al. 2019) | A, P, H |
| | | | Infrared thermography (cameras and thermometers) to capture microscale differences in surface temperatures of skin and materials and smartphone-based geospatial applications for early warning and adaptive response system (EWARS) for dengue control, e.g., MOSapp and DISapp (Scharf et al. 2008; Faruque 2019) as a microclimate-evaluating tool to estimate the thermal comfort under grazing conditions (Barreto et al. 2020) | A, H |
| Local-scale, neighborhood-scale | $10^2$ m to $10^4$ m | Air pollution, urban studies (e.g., urban design/land cover) | Passive sampler (air, soil, water) and cars with Google air pollution mappers, (Krupp 2018) | P, H |
| | | | Road Weather Information System (RWIS), urban meteorological network, NetAtmo, Mesonet (Šećerov et al. 2015) | A, P, H |
| Meso-scale, regional-scale | $10^4$ m to $10^6$ m | Urban heat island, severe weather | Remote sensing satellite thermal and multispectral imagery, mostly polar-orbiting (such as Landsat, MODIS, Sentinels, MethaneSAT, and Rapid eye) (Liu and Zhang 2011; Parlow | P, H |

**Table 2** (continued)

| Spatial scale | Area extent | Applications | Example technologies | Usage (A, animals; P, plants; H, humans) |
|---|---|---|---|---|
| | | | et al. 2014; Arellano and Cladera 2016; Bechtel et al. 2019; Abubakar et al. 2020) | |
| | | | UAV's equipped with thermal and multi/hyperspectral cameras, to acquire urban images of interest in more suitable times of the day (Gaitani et al. 2017; Burud et al. 2018) | P, H |
| | | | Dual-polarization radar (Sills and Joe 2019) | H |
| Macro-scale, synoptic-scale | $10^6$m to $10^7$m | Surface changes, trends, and extreme events (e.g., sea surface temperature in relation to fish stock and chlorophyll) | Remote sensing satellite thermal and multispectral imagery, mostly geostationary (e.g., Meteosat, GOES-16) (Kaplan et al. 1998; Reynolds et al. 2007) | A, P, H |
| | | Pest management | Predicting the humidity on leaf surface with a model based on measurements from a synoptic weather network and satellite observations (Anderson et al. 2001) | P |
| | | Wildfire monitoring | Satellite system to monitor wildfires, e.g., WildFireSat (van Mierlo et al. 2019) | P |
| | | National weather forecast | Model simulating surface-level ozone concentration (Yerramilli et al. 2012) | H |
| Global scale | $> 10^8$m | Global weather forecast, global climate change datasets | Global ERA5-HEAT (Copernicus 2020; Di Napoli et al. 2020) and the ERA5 global reanalysis (Hersbach et al. 2020), NASA GISTEMP (Hansen et al. 2010; Lenssen et al. 2019), NOAA (Smith and Reynolds 2005; Smith et al. 2008), HadCRUT4 (Morice et al. 2012) and the revision of HadCRUT by Cowtan and Way (2014), Berkeley Earth Surface Temperature (Rohde et al. 2013) and Berkeley Earth Land/Ocean Temperature Record (Rohde and Hausfather 2020) | A, P, H |

sensors can be applied to determine location, patterns in body posture, activity, and vocalization (Williams et al. 2019). For instance, body temperatures measured by miniature implanted loggers have revealed the importance of adjustments in peripheral blood flow for thermoregulation, without requiring human observation (Hetem et al. 2009). There are some limitations in the of biologgers such as the use of post hoc statistical methods to overcome the limitations of specific sensor data, like machine learning approaches to positional and accelerometer data, and the necessity of recapture of animals to recover data from on-board devices (Williams et al. 2019). Heart rate measurements can be used as a proxy for metabolism in free-ranging animals, which reveals their response to food availability in changing environments (Signer et al. 2011). Remote monitoring can be used to assess (a) thermoregulatory behavior using miniature black globe thermometers, (b) activity patterns using accelerometers, and (c) movement using GPS loggers. This can enable the assessment of how free-ranging animals adjust their activity spatially and temporally manipulate heat exchange (Hetem et al. 2012).

At the micro-scale, human thermal exposure in the built environment can be evaluated through the use of mobile custom-built human biometeorological platforms, such as MaRTy (Middel and Krayenhoff 2019). This moving observational platform enables detailed micrometeorological observations of air temperature, relative humidity, wind speed, and longwave and shortwave radiant flux densities in six directions (Höppe 1992; Ali-Toudert and Mayer 2007). This technology enables the assessment of the human health effects of different climatic elements in various urban microenvironments. It is important to note that the development of custom-made observational biometeorological platforms often requires theoretical knowledge, practical skills, and substantial financial resources that constitute a central limitation for their adoption in practice. In this respect, more affordable and accessible solutions provide less accuracy and granularity of measurement. These can include stationary devices, such as weather stations and heat stress meters, where incoming radiation is measured with gray or black globe thermometers (Thorsson et al. 2007). Other examples include infrared thermography (cameras and thermometers) that can be utilized to capture microscale differences in surface temperatures of skin and materials (Scharf et al. 2008).

## Local, regional, and synoptic scale sensing

At the local scale, a growing number of applications in different research disciplines are using UAVs (unmanned aerial vehicles) because these small instruments can carry sensors (e.g., multispectral, hyperspectral, and thermal imaging systems). These platforms enable monitoring in various environmental conditions. For example, UAVs can be used in agriculture to remotely monitor growth conditions, drought stress, and crop damage from insects. It can support wildlife monitoring and environmental enforcement (Lopez-Tello and Muthukumar 2018). UAVs can also be used in a post-disaster assessment of extreme weather events (Adams et al. 2013). Some limitations of UAV usage in biometeorological sensing include payload restriction, length of the flight, weather conditions, and interference to airspace (von Bueren et al. 2015).

Sensing at the mesoscale focuses on measuring the thermal performance of different land-use land cover (LULC) classes, to correlate meteorological conditions with health impacts. In this respect, urban meteorological networks are established to monitor regional climate and biometeorological conditions (Šećerov et al. 2015). These networks represent the conventional paradigm of observations because of the significant costs to establish and maintain them; therefore, sustainable approaches to monitor urban environments are required. The IoT is a "disruptive" technological approach (Chapman 2015) that enables the widespread use of numerous, quality-controlled devices to monitor the weather and health-related parameters in various urban environments. However, this approach has several limitations. At the regional scale, the urban fabric is quite heterogeneous, and assessing the thermal performance of different morphological typologies can be challenging because of the following: (1) most cities do not have in situ networks dense enough to provide air temperature datasets with adequate spatial resolution; and (2) there is a deficit of adequate rural reference stations due to an increase in urban sprawl, which means that formerly rural stations (particularly located in airports) have become increasingly urbanized. Such circumstances prevent detailed spatialization and study of individual neighborhood thermal performance. This research pathway uses freely accessible satellite thermal imagery to map land surface heat levels, as a proxy for human exposure to excess temperatures. In fact, freely available remote sensing satellite thermal imagery (such as Landsat, MODIS, Sentinels) provides accessible datasets with much greater spatial resolution (from 10 m to 1 km), and with global coverage (e.g., Liu and Zhang 2011; Parlow et al. 2014; Arellano and Cladera 2016; Bechtel et al. 2019). Specifically, many studies have been dedicated to infer the spatial patterns of the urban atmospheric thermal anomaly (urban heat island, UHI) by assessing the spatial patterns and intensities of the surface temperatures (surface urban heat island, SUHI).

While the use of satellite-based thermal imagery is beneficial in examining vast spatial landscapes—from forest monitoring (Dorren et al. 2003; Hansen et al. 2008) to sea surface temperature dynamics (Kaplan et al. 1998; Reynolds et al. 2007), from geologic surfaces differentiation (Syvitski et al. 2012) to fire detection (Giglio et al. 2003)—its application to human heat-related health research requires an understanding of two circumstances. Firstly, UHI effect is not in and of itself damaging to human health, despite controversy on the subject (e.g., Manoli et al. 2020; Martilli et al. 2020). Although several research studies have reported an increase in UHI intensity during heatwave events, or event UHI-related mortality (Heaviside et al. 2016, Lemonsu et al. 2015, Paravantis et al. 2017, Tan et al. 2010), it is actually the heatwave event itself (which is a widespread regional phenomenon, not restricted to the urban areas) that causes health-related consequences. As such, the potential contribution of the urban thermal anomaly to excessive heat exposure must be acknowledged. It requires further investigation into examples of case study cities across climate regions to be assumed an overall certainty. Secondly, even in cases where UHI increases under heatwave conditions have been reported, one must consider that surface and air UHI are not synchronous, and the former is not necessarily a proxy of the latter. In short, there are several limitations to using satellite thermal imagery for mesoscale urban climate studies. For urban areas, the sub-kilometer spatial resolution is of greatest interest to distinguish the thermal performance of different built-up densities and morphologies. For example, only at the 100-m scale is it possible to detect and assess the impact of neighborhood scale green areas, such as small parks and community gardens. As such, only Landsat satellites offer this spatial resolution in their thermal bands, but it presents challenges for continuous monitoring, which is especially relevant considering the frequency of non-viable scenes due to extensive cloud cover. Another freely available alternative is shorter range satellite-based thermal imagery that ranges from 1-km resolution (e.g., MODIS, Sentinel 3 SLSTR) to 5 km (e.g., SEVERI) or more. Although Landsat 5-8 imagery has an adequate spatial resolution, it is acquired during the morning which is least suitable for urban climate research, as surfaces in the built environment are not yet warm enough to show a significant thermal signal, especially in drier climates where cities are not surrounded by dense tree cover (e.g., Oliveira et al. 2020.

The ideal method to assess UHI from surface thermal imagery is to either have enough daily samples (e.g., hourly) to compute a daily SUHI cycle, or to use that data to compute the flux components of the urban energy balance (UBE): heat storage, sensible heat, and latent heat components. The UBE approach has evolved (Oke 1982; Oke 1988; Stewart et al. 2014; Oke et al. 2017) and its application to remote sensing data has been explored by several urban climate research groups (Rigo et al. 2006; Rigo and Parlow 2007; Wicki et al. 2018; Chrysoulakis et al. 2018) with encouraging results. Nevertheless, the main challenge is the need for in situ monitoring to validate approaches. Flux towers are one method of validating satellite-based results but are difficult to access because they require substantial financial resources and appropriate site location (Rigo and Parlow 2007; Wicki and Parlow

2017; Wicki et al. 2018). In cases where flux towers have been constructed (e.g., UrbanFluxes project), there are also challenges in evaluating the accuracy of satellite-based results (i.e., each pixel covering several hundreds of square meters) given urban spatial heterogeneity.

Recent trends in both technological solutions and data analytics offer new pathways to overcome monitoring challenges. Smaller scale unmanned autonomous vehicles (UAVs) equipped with thermal and multi/hyperspectral cameras can collect urban imagery at more suitable times of the day (Gaitani et al. 2017; Burud et al. 2018). In addition, merging different data products can generate synthetic remote sensing-equivalent imagery, based on complementary datasets including satellite imagery from multiple sensors with different spatial and temporal scales, and local vector-based geo-information such as built-up contours and land use-land cover classification (Zurita-Milla et al. 2009; Weng et al. 2014). New satellite systems such as WildFireSat can reduce the time period required to access the data after data acquisition from hours or days down to 30 min (van Mierlo et al. 2019), allowing for better decision-making in emergency preparedness and forest fire control. Reflective remote sensing (~ 400–2500 nm) can increase the performance of agroecosystem modeling by providing canopy state variables at a spatial coverage and at spatial and temporal resolutions that would be impossible to achieve via ground observations or field campaigns (Dorigo et al. 2007). This supports management strategies that maximize crop production while minimizing environmental impacts.

### Global scale sensing

At the global scale, the Global ERA5-HEAT (Human thErmAl comforT) represents state-of-the-art bioclimatology data record production. This dataset provides a complete historical reconstruction for a set of indices ($T_{mrt}$ and UTCI) representing human thermal stress and discomfort in outdoor conditions since 01/01/1979 to near real-time. It is regularly extended as ERA5 data becomes available. Data is gridded with horizontal resolution 0.25° × 0.25° and has global coverage, except for Antarctica (90 N–60S, 180 W–180E) and provides hourly temporal resolution of data (Copernicus 2020). This dataset is computed using the ERA5 reanalysis from the European Centre for Medium-Range Forecasts (ECMWF). ERA5 combines model data with observations from across the world to provide a globally complete and consistent description of the Earth's climate and its evolution in recent decades (Copernicus 2020). This dataset represents an important technological opportunity for assessing trends in human thermal comfort conditions as the past few decades have been marked by a changing climate. Furthermore, Copernicus forecasts UV index values, European air quality, and worldwide long-range transport of pollutants.

RapidEye Satellite is another satellite system equipped with multi-spectral push broom sensors. It has the ability to acquire high-resolution data (5 million km$^2$ per day). The satellite is radiometric, sensor, and geometrically corrected. It is also aligned to a cartographic map projection. This can remove distortions caused by terrain (RapidEye 2016).

Another global scale sensing opportunity is the MethaneSAT satellite that will be launched in 2021 by the European Space Agency to continuously collect data on the magnitude and location of methane emissions around the planet. This will enable the identification of methane hotspots and monitoring of emission reductions over time (Krupp 2018). It will employ a highly sensitive spectrometer that measures light at the specific wavelengths where methane absorbs light within the shortwave infrared spectrum and detects differences in methane concentration as low as 2 parts per billion (ppb). MethaneSAT's small pixel size (1–2 km$^2$), and wide view path (200 km$^2$) will be able to quantify small emission sources over large areas with finer resolution data that will allow larger emissions to be pinpointed to within 400 m of their source. This makes it preferable to the greenhouse gas satellite (GHG SAT) and is a key tool for the identification and reduction of methane emissions (Krupp 2018).

## Sensing parameters

### Environmental and meteorological sensing

In surface measurements, there has been a systemic shift from human observation of weather elements to automated weather stations around the world (van der Meulen 2017). The meteorological parameters recorded include air temperature, precipitation, wind speed and direction, snow depth, soil temperature, solar radiation, visibility, cloud ceiling, and current weather (Leung and Gough 2016; Leung et al. 2020b). There are both positive benefits and negative impacts on the automation process of weather stations. Positive benefits include improved measurements at remote locations, higher frequency of observations (e.g., hourly precipitation amounts, gust speed), observations not reliant on personnel, reduction in human error, and real-time reporting (Sabatini 2017; van der Meulen 2017; Leung et al. 2020b). Negative impacts include reduced accuracy for some parameters (e.g., visibility, types of cloud, snow depth), inability to measure trace amounts of precipitation, false positives of snow depth due to weed growth underneath the sensor, lack of distinction between various types of precipitation (rainfall, freezing rain, hail, snowfall, etc.), power or transmission outages resulting in loss of data, and unclear impacts on long-term climate records due to a change in instrumentation (e.g., switching from a handheld thermometer to a digital thermometer) (Milewska and Hogg 2002; Follett et al. 2015; Sabatini 2017; van der Meulen 2017; Leung et al. 2020a). These impacts could introduce non-climatic, artificial bias in the climate records, some of which can be addressed by the homogenization of the data (Squintu et al. 2019).

Radiation is a decisive parameter in the study of outdoor thermal comfort (Brown and Gillespie 1995; Thorsson et al. 2007; Kántor et al. 2014; Lee et al. 2014; Manavvi and Rajasekar 2020); however, it remains the most elusive element of the landscape (Brown and Gillespie 1995). Measuring radiation in open spaces is complex owing to heterogeneous long and short-wave radiant flux densities, shading, and terrain. Radiation instruments can be classified based on the type of variable to be measured, field of view, spectral response, and intended use (WMO 2014). Instruments used for measuring radiation include pyranometers, pyro-heliometers, and sun-photometers. Net radiometers estimate net radiation; albedometers estimate the albedo of surfaces, while sun trackers measure global, diffuse, and direct irradiance.

Pyranometers are characterized by the sensors used, specifically thermal sensors (thermopile) and photovoltaic (PV) sensors (Alados-Arboledas et al. 1995). Thermal sensors have a nearly constant spectral sensitivity for the whole solar spectral range and therefore enjoy wide application (Alados-Arboledas et al. 1995). Photovoltaic radiation sensors on the other hand are the simpler and cheaper alternative. Photodiode-based pyranometers have a response time of 10 μs making them suitable for measuring rapid changes in radiation. Using PV cells as radiation sensors has limitations. Firstly, there is a risk of limited and non-uniform spectral response of silicon cells. Secondly, the thermal dependence of these sensors (about 0.15% per °C) can cause a change in the sensitivity in mid-latitude regions (Michalsky et al. 1987).

Also, it is crucial to note that most radiation sensors are not absolute and require calibration. The uncertainty of the radiation sensors depends upon resolution, changes in sensitivity due to environmental variables, deviation of spectral response, and time constant of the instrument (WMO 2014). Certain instruments perform better for particular climates, irradiances, and solar positions. Instruments for measuring radiation should be chosen carefully in accordance with their end-use and intended location of application (WMO 2014). Furthermore, procurement and deployment of these instruments under various conditions involve substantial costs thereby limiting concurrent measurements.

Emerging technologies for measuring radiation have begun focusing on developing low-cost options (e.g., Martínez et al. 2009). Loveday et al. (2019) have developed iButton radiation sensors to measure albedo. This sensor comprises a silicon chip contained in a stainless steel can (17 mm in diameter and 6 mm high), which it uses as a communications interface (Loveday et al. 2019). Mean radiant temperature ($T_{mrt}$) is one of the most important meteorological parameters governing human energy balance (Thorsson et al. 2007) and is among the parameters necessary in the calculation of the human thermophysiological stress indices, such as PET (Höppe 1999) and the UTCI (Bröde et al. 2012; Jendritzky et al. 2012). There are different technological solutions to acquire $T_{mrt}$ data. Instrumentation to measure this data includes globe thermometers, pyranometers, and pyrogeometers. These instruments have enabled researchers to overcome the existing knowledge gap in the measurement accuracy of different radiation fluxes that influence human thermal exposure and thermal comfort outdoors.

In addition to $T_{mrt}$, measurements of wind speed and surface and air temperature are important in the assessment of urban bioclimate and outdoor thermal comfort. Measurements of wind speed are often performed using a large variety of anemometers with the most common being the two-dimensional cup anemometer, followed by the heated sphere. On the contrary, the three-dimensional measurements of the wind speed are rare. Because wind speed is a critical variable in assessing the thermal comfort, accurate measurements are required to overcome limitations in certain instruments (e.g., cup anemometers are inappropriate at low wind speeds) (Johansson et al. 2014). For the measurement of air temperature, several aspects should be considered: (i) proper shielding of the sensor to minimize radiative exchange (ISO 7726 1998; WMO-No. 8 2008); (ii) proper ventilation of the radiation shield (WMO-No. 8 2008); and (iii) account for instrument thermal inertia (ISO 7726 1998; ASHRAE 2001) (Johansson et al. 2014). For analysis of surface temperature, infrared thermography (e.g., portable infrared thermometer, thermal infrared imager, forward-looking infrared radiometer (FLIR)) (Scharf et al. 2008; Kuang et al. 2015) and remote sensing (e.g., LANDSAT-8, MODIS LST (Bechtel et al. 2019; Geletič et al. 2019) are used to provide temporal and spatial resolution for assessment of surface temperature changes.

Passive air samplers collect pollutants over time. They are suitable for deployment using a variety of structures (e.g., trees, utility poles, traffic lights) in remote or urban locations. Since they capture pollutants passively by trapping them in a filter or orifice, they do not require electricity or labor to operate continuously. Passive air samplers can measure different pollutants, such as polycyclic aromatic hydrocarbons (PAHs), polychlorinated biphenyls (PCBs), and gaseous mercury (Eng et al. 2014; Jeon et al. 2019). Air pollutants can also be measured with active air samplers (Anderson and Gough 2020). Measurements can be undertaken for gaseous air pollutants including nitrogen dioxide, ozone, and carbon dioxide among others (Okeme et al. 2016; Anderson and Gough 2020). These measurement technologies are essential to biometeorological research on linkages between air pollution, urban development, and human health outcomes. Passive water samplers can measure heavy metals, flame retardants, antibiotics, and others (Brumbaugh et al. 2002; Chen et al. 2012; Cristale et al. 2013).

Plants are an integral part of biometeorological studies. Studies pertaining to plants in biometeorology require data from various sources including meteorological parameters (e.g., air temperature, rainfall, relative humidity, wind speed and direction, leaf wetness, and solar radiation), physical parameters (e.g., $CO_2$ concentration, soil structure), and biological parameters (e.g., observed symptoms, crop monitoring parameters) (Orlandini et al. 2009). Lysimeters are used to measure evapotranspiration of plants and come in types: weighable (percolation type) and non-weighable. Large-area percolation type lysimeters are used for water budget and evapotranspiration studies of mature and deep rooting vegetation cover (WMO 2014). On the other hand, basic lysimeters can be used in areas with bare soil or grass and are easy to install with low maintenance costs. Practical details that relate to the choice of the lysimeter wall material, depth of the lysimeter, and minimization of the soil and plant disturbance during extraction must be considered for application. Custom-made mini-lysimeters have been used in studies estimating the influence of trees and grass on outdoor thermal comfort in a hot-arid environment (Shashua-Bar et al. 2011). Transpiration from trees can also be measured through the sap flow (i.e., thermal dissipation method) (Gash and Granier 2007). The thermal dissipation probe (Granier 1985) is widely used to estimate tree transpiration. It is simple to build, easy to install, requires low-energy supply, and is relatively inexpensive (Pasqualotto et al. 2019).

Further parameters such as chlorophyll and nitrogen can be measured through the use of spectral sensors (Peng et al. 1995; Ling et al. 2011). These sensors are lightweight, easy to use, and are handheld. They can be easily coupled with apps in a smartphone for enhanced use (Hariadi et al. 2018). A limitation in the use of these sensors however is that they do not give value for the whole plant, requiring a computational average. In addition, they are costly and application varies based on the type of vegetation structure.

Parameters such as leaf area index area crucial in plant studies. Leaf area index (LAI) can be measured through the leaf area meter (Pandey and Singh 2011; Dufrêne and Bréda 1995; Marenco et al. 2009). Additionally, cost-effective photovoltaic leaf area meters have been developed (Igathinathane et al. 2008). Recent research has attempted to improve the leaf area index estimates by utilizing the gap fraction method (Martens et al. 1993; Phattaralerphong et al. 2006). The aforementioned method has been used widely for the ecophysiology of agricultural crops (Hicks and Lascano 1995), boreal forests (Chen et al. 1997), and deciduous stands (Chianucci and Cutini 2013).

Soil sensing is an important component of biometeorological research as it focuses upon the interactions between the human, animal, and plant populations across time scales. The synergistic relationship between soil, water, and climate regulates vegetation. Soil moisture has implications for agriculture, ecology, wildlife, and public health. After precipitation, it is the most important connection between the hydrological cycle and human, animal, and plant life (Lakshmi 2013). Soil moisture content as a function of depth is an important parameter for biometeorological research but its application varies. For example, evapotranspiration models generally pertain to a shallow depth (i.e., tens of centimeters) while agricultural applications require moisture information at root depth (i.e., order of a meter), while atmospheric general circulation models incorporate a number of layers down to a few meters (WMO 2014). Soil moisture is highly variable in both space and time; therefore, it can be difficult to measure soil moisture on the continental or global scale as needed by researchers (Lakshmi 2013). Space-based remote sensing of soil moisture is one method that provides surface soil moisture observations on a global scale.

Researchers have developed various techniques for measuring soil moisture including thermo-gravimetric (Robinson et al. 2008; Hillel 2013), neutron scattering (Jayawardane et al. 1984; Fityus et al. 2011), soil resistivity (Amer et al. 1994), and dielectric techniques (Campbell 1990; Baumhardt et al. 2000; Hilhorst 2000; Schwartz et al. 2008). Additionally, soil water potential measurements can be performed by several indirect methods using tensiometers, volumetric water sensors, resistance blocks, soil profiling probes, and soil psychrometers. Observations of soil moisture at a point scale are very sparse and observation networks are expensive to maintain (Lakshmi 2013). Soil moisture sensors are useful for studying processes at a smaller scale, but large numbers are required for a comprehensive understanding. Space-based remote sensing of soil moisture provides surface soil moisture observations on a global scale. For passive remote sensing of soil, four principal types of sensors are as follows: (i) optical remote sensing with a limited number of bands (e.g., SPOT, ASTER, and LANDSAT); (ii) optical remote sensing based on hyperspectral sensors, particularly adapted for soil texture description; (iii) optical remote sensing with a thermal infrared band, adapted for soil temperature estimation; and (iv) passive microwave remote sensing adapted to soil moisture and vegetation estimation (Zribi et al. 2011).

Soil temperature is another crucial parameter in soil studies. Thermocouples, resistance-temperature detectors (RTD), thermistors, integrated circuit sensors, and infrared thermometers are commonly used sensing tools for measuring soil temperature (Berard and Thurtell 1990). The challenges involved with soil temperature measurements include non-uniform temperature distribution, low resolution, self-heating effect, and shortened sensor life span (Aniley et al. 2017). A bent-stem soil thermometer is often used to measure soil temperature between the ground surface and a depth of 20 cm below ground (WMO 2008); however, such a thermometer is exposed to sunlight and needs to be removed in harsh conditions (Berard and Thurtell 1990; Aniley et al. 2017). Surface soil temperature can be measured using an infrared temperature sensor (Wang et al. 2015) or in situ sensors such as type E thermocouples and thermistors. Thermistors have several potential advantages such as higher temperature capability, high sensitivity, simple construction, and low cost (Aniley et al. 2017). Additionally, ultra-narrow field of view infrared radiometer sensors are being employed in terrestrial surface (e.g., soil, vegetation, water, snow) temperature measurements in energy balance studies. One challenge in using thermistors is that servicing and maintenance of buried instruments can disturb the soil and introduce noise to the data. The choice of a type of sensor depends on the equipment available, cost, application, and accuracy desired (Berard and Thurtell 1990).

## Physiological sensing

Both human and animal studies in biometeorology use measurements of physiological parameters as health and performance indicators to examine how weather, climate, seasonality, and changes in the immediate environment affect health, productivity, and well-being. A body of literature examines how seasonal variations or environmental extremes (e.g., high or low ambient temperatures, high humidity, high altitude) affect heat stress levels, sleep patterns, and chronic or acute diseases (Bhattacharyya et al. 2008; Scharf et al. 2008; Schneider et al. 2008; Tsuzuki et al. 2008; Kanikowska et al. 2009). Other studies examine how specific interventions in patients' daily routines can affect their recovery, for example baths with high $CO_2$ concentrations, baths with high or low temperatures, negative air ions, and exposure to nature (Yamamoto and Hashimoto 2007; Iiyama et al. 2008; Suzuki et al. 2008).

Typically, combinations of physiological variables are measured to assess subjects' responses to environmental stressors. Tympanic, skin, sublingual or rectal temperatures, and sweat rates are common variables measured in humans and animals to evaluate heat stress and thermoregulation (Scharf et al. 2008; Lee et al. 2009; Mader et al. 2010; Wakabayashi et al. 2011). Temperature is measured with wearable or small portable devices such as thermistors, infrared and electronic thermometers, and sweat rates are measured with capacitance hygrometers. Heart rate, blood pressure, and blood flow help to assess body responses to various environmental stressors and are measured with wearable watches, tachometers, and sphygmomanometers for heart rate and blood pressure and laser Doppler flowmetry for blood flow (Iiyama et al. 2008; Suzuki et al. 2008). Blood samples are utilized in human and animal biometeorological studies to identify indicators of stress in the body chemistry with levels of cortisol and hematocrit being the most common (Antonelli and Donelli 2018; Pereira et al. 2008).

However, there are a variety of measures tested depending on the study goals. Studies that examine sleep patterns and stress levels due to climate- or weather-related factors use cardiac output measured with portable or wearable ECG devices (Bhattacharyya et al. 2008; Delyukov et al. 2001). Other variables measured include sleep, brain and muscle activity, saliva and urine, oxygen levels, and respiration and expiration levels (Bhattacharyya et al. 2008; Celec et al. 2009; Taniguchi et al. 2011; Wakabayashi et al. 2011). Certain physiological parameters, such as skin temperature or heart rate, can be easily measured with wearable or portable devices, while obtaining others require lab tests and controlled settings. The complexity of the experiment and the type of equipment used will affect the data accuracy, sample size, and replicability. Developments in non-invasive techniques and wearable devices for obtaining physiological measurements can help to overcome some of these limitations. In addition, opportunities to collect physiological data from ubiquitous wearable devices such as smart watches, present a promising new direction in research on human and animal biometeorology.

Lack of standardization for studies in semi-controlled experiments is an ongoing concern. The frequency and time of measurements, minimal amount of data points, number of participants, and duration of the experiments vary widely between the studies making it difficult to draw comparisons among regions and populations (Johansson et al. 2014). Selection and use of instruments are guided by the international standards and national guidelines, such as ISO 7726 (2001) and ASHRAE Handbook of Fundamentals (ASHRAE 2001). These standards specify the required and desired accuracy and response time. However, some of the guidelines might be difficult to follow in the field experiments. For instance, for thermal comfort studies, it is recommended to position the thermal sensor at 1.1 m, which is a core of a standing person (ISO 7726 2001); but in reality, sensors are often placed at above 2 m height for long-term data collection to avoid obstruction of pathways and prevent vandalism. Instruments have to be selected in accordance with appropriate standards and regularly calibrated to maintain specified accuracy. In addition, instruments need to be properly positioned, shielded, and ventilated to avoid under- or overestimation. For instance, air temperature and humidity probes should be protected from direct sun exposure (Johansson et al. 2014). Sensors located close to roads or air-conditioned buildings can be affected by waste heat or escaped cool air. Response time is another important concern for decisions on quantity and time interval of measurements. For instance, quick response time and larger time interval are necessary for wind measurements to ensure accuracy and capture of low and high winds. Three directional wind measurements are ideal for optimal accuracy; cup and propeller anemometers are not effective for areas with low wind speed (Johansson et al. 2014). Globe radiation measurements are affected by the size and color of the globe (Teitelbaum et al. 2020). Smaller black globes commonly used in Kestrel Heat Stress Trackers tend to overestimate globe temperature in the sun due to the globe overheating (Kántor and Unger 2011; Middel et al. 2016). Additionally, smaller globe size is more affected by the wind variations and can lead to inaccuracies on globe temperature measurement (Johansson et al. 2018). The flat gray color of the globe better represents characteristics of human clothing and skin, while black-colored globes tend to overestimate the influence of short-wave radiation (Thorsson et al. 2007).

Considerations for individual environmental exposure wearable devices include convenience for participants, safety, participants' anticipated behaviors, and sensor placement. Sensors need to be worn outside of bags and clothing to avoid contact with skin or sweat. Consistent placement among participants is important to ensure comparability (Kuras et al. 2017). Accurate measurement of body temperature in uncontrolled or semi-controlled environments remains a challenge. Rectal temperature is the most accurate method to measure core temperature, but it is not suitable for outside the lab environment. Telemetric pills are one possible alternative. Some of the accuracy concerns are that the exact position of the pill in the intestinal tract cannot be controlled; therefore, differences in position between subjects can affect the temperature (Dougherty et al. 2009). In addition, the telemetric pill is affected by the ingestion of cold and hot fluids (Dias and Paulo Silva Cunha 2018).

## Sensing approaches

### Wireless sensor networks and the internet of things

Many sensing technologies can be enhanced through the use of wireless sensor networks (WSNs) to overcome the challenges of analogue sensors mainly long time queues for data acquisition, processing, and analysis. The WSNs refer to spatially distributed sensors that monitor specific information (e.g., air quality, weather) and cooperatively convey the data to a central base station (i.e., sink) using wireless connectivity (Matin and Islam 2012; Flammini and Sisinni 2014). For example, WSNs have proved to be effective in real-time communication of environmental and meteorological data across vast areas (Yahya 2020). The WSNs as shown in Fig. 3 are composed of "nodes" and a base station or gateway, which enables acquisition and transmission of field observations to a data storage and processing facility, and further enables end users to utilize the field observations or derived products from devices and for diverse applications (Flammini and Sisinni 2014; Kocakulak and Butun 2017). Some of these observations utilizing WSN include marine environment monitoring (Xu et al. 2019b), monitoring and controlling greenhouse environmental conditions (Ferentinos et al. 2017), and forecasting apple disease (Nabi et al. 2020). The "Internet of Things" (IoT) is defined as any object that is aware of the context of its location with the capacity to communicate through the internet, at any time and location. Advances in the use of the IoT as a platform for WSN has rapidly progressed and increased the usefulness of near real-time data for understanding the effect of rapid environmental change (Chapman 2015). Application of IoT sensor networks for near real-time data acquisition overcomes the shortcomings of traditional analogue techniques that are prone to vandalism, drift, and have long time queues for data processing.

Configuration of IoT-WSN varies with respect to data requirements, range of communications, energy consumption, licensing restrictions, and setup costs. These limitations can impact the application of collected data through observation frequency, number of monitoring stations, and anonymization of data. The long range-wide-area network (LoRaWAN) is a type of low-power wide-area network (LPWAN) that permits sensor nodes to communicate over long distances using radio networking technologies (Khutsoane et al. 2017; Mdhaffar et al. 2017). LoRaWAN removes the requirement for conventional networking connectivity, such as WiFi, SIM cards, or Ethernet cables, thus reducing the hardware and operating costs of dense sensor networks. The data is transferred to the internet via a gateway, and the network can be used as an "Open Network" through organizations such as "The Things Network" that enable citizen science (Khutsoane et al. 2017; Mdhaffar et al. 2017) or to provide timely weather information to rural farmers in developing countries (Reda et al. 2018). Although IoT-WSN is being increasingly operationalized for military, industrial, and smart city use, its scope of application is still limited within biometeorology. Moreover, future efforts aimed at enhancing the use of IoT technologies for biometeorology ought to address concerns of low sensor accuracy and the need for standardization of data collection and analytics.

### Crowdsourcing

Chapman et al. (2017) and Meier et al. (2017) define crowdsourcing based on Muller et al. (2015) as the collection of atmospheric data from public sensors that are connected to the internet. Zhu et al. (2019) delineated four different types of potential providers of crowdsourced data namely (1) smart embedded sensors, (2) social networks, (3) sensors provided by meteorological services, and (4) citizen-based science. People are not only message receivers but also perceive and produce weather and environmental information through social media (Zhu et al. 2019). For example, social media channels were used by extracting keywords or hashtags used in posts to evaluate severe weather events or rare atmospheric

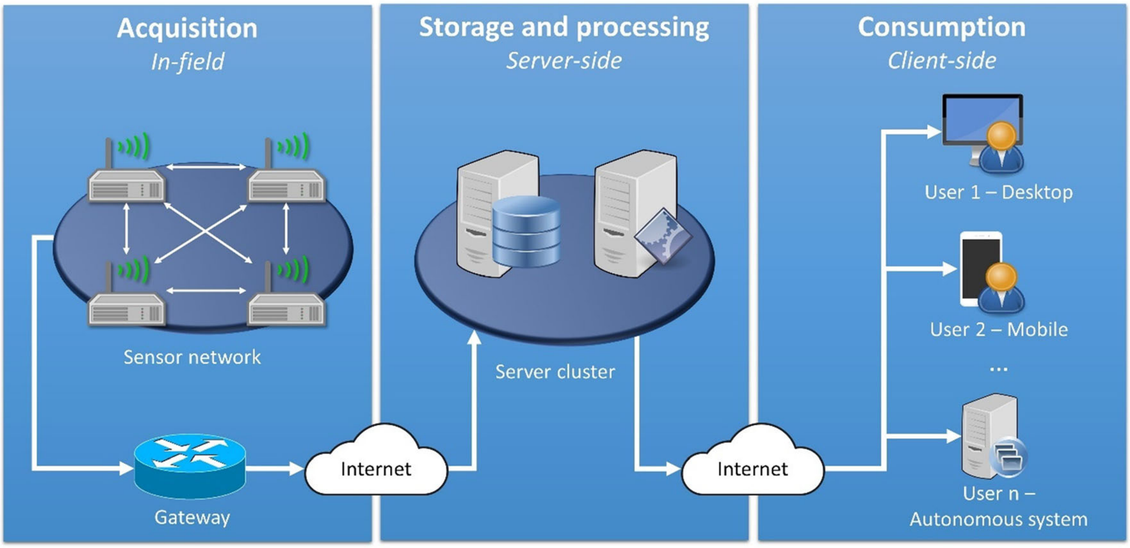


**Fig. 3** The IoT end-to-end pathway of data transmission (illustration based on Kocakulak and Butun 2017)

phenomenon in central Canada and the United States (Leung et al. 2017). In Europe, forest fires are also monitored through blogs, tweets, and photos (De Longueville et al. 2010). The inclusion of subjective data such as opinions, reactions, emotions, and feedback on the weather can inform emergency management and disaster planning (Zhu et al. 2019). Crowdsourcing initiatives can also enable sensing of climate change impacts on plants and animals, and indirectly on humans. Two Dutch citizen science projects to monitor ticks collected nearly 50,000 geo-located tick bite reports from 2006 to 2016 (Garcia-Marti et al. 2018). Crowdsourced information can support mapping of hazards, risks, and potential exposure.

Particularly in cities with high spatial variability, there is a need for high spatial resolution spatial weather and climate data. Using crowdsourced data from citizen weather stations such as Netatmo in combination with high-quality meteorological data is an effective way to overcome the challenges presented by those heterogeneous urban environments. This heterogeneity includes microclimates and variability in temperature, precipitation, air quality, and wind speeds (Chapman 2015). These high-spatial-resolution technologies can contribute to increasing urban resilience through improved accuracy of predictions leading to enhanced monitoring capabilities, and emergency preparedness. Crowdsourced weather stations are used globally in the analysis of spatial variability in near-surface air temperature (Chapman et al. 2017; Leibovici et al. 2017). The benefits of crowdsourced data include widespread coverage, low cost of instrumentation, and real-time data collection.

For example, Netatmo and Wunderground stations have been installed in highly urbanized areas which makes the dataset suitable to analyze variability between various urban microclimate conditions. Other aspects, such as the cooling effect of urban parks cannot be analyzed directly from the data, as stations are almost exclusively installed in built-up environments (Meier et al. 2017). The basic Netatmo and Wunderground weather station packages, measure air temperature, humidity, pressure, noise level, and carbon dioxide concentrations. Advanced modules also include other parameters such as precipitation and wind. Weather station operators can decide if they wish to publish their datasets, which can be freely accessed by the public, however, little metadata is available for individual stations (Chapman et al. 2017). These sensors have been used in human biometeorological research across various European cities (Chapman et al. 2017; Meier et al. 2017; Fenner et al. 2017; de Vos et al. 2017; Nipen et al. 2020; Feichtinger et al. 2017).

The crucial deficit in crowdsourced data is the unknown data quality. These data need to be quality controlled to account for inconsistent metadata, low data availability, poorly maintained/calibrated instruments, and placement of modules (e.g., exposure to direct solar radiation). Several studies have developed post-processing methods to control the data quality of Netatmo networks (Meier et al. 2017; Chapman et al. 2017; Napoly et al. 2018; Nipen et al. 2020). Additionally, Meier et al. (2017) evaluated the accuracy using comparative measurements in a climate chamber and in the field. They confirmed the average accuracy level of ± 0.3 K but revealed that temperature offsets of up to 1.3 K occurred frequently and that four of the seven tested sensors showed a warm bias of nearly 0.5 K. It is also important to keep in mind that if the instruments are not carefully maintained and calibrated, this could lead to a possible drift toward poorer data quality over time (Meier et al. 2017). Furthermore, there is an element of uncertainty with respect to the continuity of sampling and duration from these crowdsourced devices and networks. These ad hoc devices and networks are typically not intended for long-term data collection compared to conventional weather stations (Jean 1991). Conventional weather stations have the advantage of having long time series, more stable funding, regular maintenance, and operational standards as set out by the WMO (Jean 1991). This allows data to be exchanged globally and used in meteorological forecasting and research models. These ad hoc devices and networks can supplement data collection undertaken by conventional networks.

## Discussion

### Accuracy, guidelines, and standardization

Acquiring spatially and temporally congruent information on how weather and climate influence human, animal, and plant health can present challenges; however, it is crucial to understand the limitations of current, new, and emerging technologies. For example, a heated tipping bucket rain gauge is suitable for tropical climate or summer field season on a local to regional scale but may not be suitable for snow studies due to the evaporation loss from the heating component in the gauge (Savina et al. 2012). The use of different technological solutions or their combination (e.g., sensing and modeling) should facilitate this task providing the most significant weather data for human, animal, and plant health, such as radiation, wind, temperature, and humidity (Leung et al. 2020b). Detailed weather and climate datasets should be linked with biophysical indicators and psychological responses (Oke et al. 2017). For example, outdoor thermal comfort indices and human outdoor thermal comfort models have been developed to study the link between weather and psychological parameters such as ambient stressors, physical exertion, outdoor human comfort, and preexisting health conditions (Epstein and Moran 2006).

Review studies by Johansson et al. (2014) and Potchter et al. (2018) found a great variety of instruments (with diverse accuracy) and methods (without standardization) used to measure meteorological variables and access outdoor human thermal perception. The use of numerous methods makes it difficult to compare results from various studies and accordingly there is a need for standardization and guidance regarding how to conduct field measurements and surveys in outdoor environments. These standards and guidelines should provide advice regarding the choice of measurement sites, type and accuracy of sensors (especially for $T_{mrt}$ and wind speed), statistical methods, and unifying outdoor thermal comfort questionnaires. Furthermore, evaluating the human comfort indoor and outdoor is challenging due to a large number of physiological variables (e.g., thermoregulation, energy balance (Chen and Ng 2012), sweat rate, metabolic response (Lenzholzer and de Vries 2020), physiological adaptation or acclimatization (Hondula et al. 2015), in addition to environmental and psychological variables, that influence thermal, visual, and aural comfort (Jayathissa et al. 2020)). The acquisition of physiological data as an indicator of human perception is complex, particularly in real-world settings where perception is influenced by various factors (Bell et al. 2001), such as changes in the environment or in the field-of-view of the investigated person (Ojha et al. 2019). Accordingly, personal exposure should be combined with information about various physiological susceptibility factors (Kuras et al. 2017). The present study supports the previous conclusions regarding the urgent need for standardization of methods and techniques in contemporary biometeorological research, by accounting for different temporal and spatial scales across diverse climates and regions.

### Access to technological advancements

Gaps in technology present another challenge. Technology is linked to economic development. The type and scale of technology used in biometeorology are dependent upon the circumstances, capacity, and resources of the interested researcher (Kesici Çalkan 2015; Steenhuis and de Bruijn 2012). While global scale satellite data is accessible, access to higher resolution data is dependent on available resources. In addition, the lack of infrastructure (e.g., electricity and data coverage) in remote areas and isolated communities also limits the use of certain technologies. Power may be unreliable or intermittent and data transmission can be slow and expensive in less built-up areas. Technologies such as automated weather stations or other instruments that require constant electrical access and frequent data transmission to operate can create barriers to widespread adoption and dissemination.

While existing technologies enable data production at high spatial and temporal resolutions, there is a significant challenge in materializing all its potential—the so-called digital divide. Originally, this concept was conceived to distinguish between people with and without physical access to Information and Communication Technologies (ICTs), but since its introduction, it has evolved to include other aspects such as the technical capacity to utilize them (Longo et al. 2017). In this regard, the differences between the global north and south regarding access to economic resources and training might limit researchers in developing countries to the usage of old technologies. As such, the potential benefits of newer technologies remain a privilege for researchers in developed countries. Populations of the digitally invisible especially in low and middle-income countries (LMIC) countries are characterized by lack of access to and quality of technology, poor infrastructure, inadequate computer and digital skills, and language barriers (George 2020). They lack smartphones, credit cards, and internet connectivity, in addition to living beneath the concentration of sensors and data capture points (Longo et al. 2017). This digital divide is caused by inequality in the ability to use technology, access to social support networks, and quality of available technology (Diaz Andrade and Techatassanasoontorn 2020).

Other research challenges include the availability of funding, access to expertise in data collection and processing, and technical skills training. Vendors for biometeorological instruments and engineers for their installation, calibration, repairs, and maintenance are difficult to access in most low and middle-income countries (LMIC). Similarly, training and re-training of experts on how to interpret instructions for the use of instruments is a required standard for data collection in meteorology for professional competence, particularly with the invention of new instruments. This standard is lagging in most LMIC because of funding. Together they have an influence on the data quality from these regions. Barriers to the adoption of new biometeorological technologies can be reduced for countries with capacity challenges through membership in global research networks and collaborative research partnerships. Free-for-research platforms can also provide a mechanism to overcome the digital divide between the global north and south. For example, free satellite images can be downloaded from Planet (Kirschbaum et al. 2019), processed in Google Earth Engine (GEE) to map agricultural land in southern Mali or the loss in green and gray spaces areas in urban cities (Clinton et al. 2015; Aguilar et al. 2018). Satellite images that are provided by GEE are ideal datasets and biometeorological assessments of agricultural fields at the local scale. For example, Rapid Eye Satellite was used in the village of Bourasso in rural Burkina Faso to investigate child malnutrition by linking satellite images with individual fields to reveal crop yield estimation of family garden plots (Sorgho et al. 2017). The scarcity, randomness, and inaccessibility of in situ continuous climate data and the estimation of global air temperature in various parts of the world have been solved with the emergence of satellite data (Sobrino et al. 2020).

## Access to personal data

Access to individual-level data has become more prevalent in health-based research through wearable devices such as smart watches, skin tattoos, or smartphones. Biometric and georeferenced data are two kinds of collected data from such technologies that can be useful in biometeorological research but have the potential to be personally invasive. For example, researchers need to obtain informed consent from participants for any studies involving human subjects. Participants must be provided with an opportunity to accept, decline, or withdraw from the study (Crow et al. 2006). Besides, there is a need to restrict the access of collected data, particularly if it is attributable to the user (Miller 2008). Social media posts are useful in tracking biometeorological data; however, scraping/crawling social media posts and tweets may violate the service provider's terms and conditions for using their websites. For example, Section 4 of Twitter's terms and conditions states that "scraping the services without the prior consent of Twitter is expressly prohibited" (Twitter 2020). Similarly, other data sources may also impose restrictions on the use of their data, such as prohibiting commercial use. In addition, digital data solely based on those wearable devices or smartphones may be biased and only offer a partial picture of the reality of the digital invisible—those people that do not own such devices or are less connected for different reasons such as poor bandwidth, age, neglect, or underrepresentation (Longo et al. 2017).

## Data collection and storage

Most new sensors offer wireless and near real-time data collection and storage. The basic steps for data transmission include the following:(1) data collection using data loggers or communication hardware; (2) data management with network servers, data quality checks (quality assurance/quality control; QA/QC), pre-processing data, and archive data repository; (3) data display using visualizations, near real-time displays, graphs, maps on websites or files for download; and (4) data usages for the end users who can be researchers, the general public or stakeholders (Muller et al. 2013). Siting and placement of sensors and measurement technologies are crucial for quality data collection. Guidelines and standards rarely exist for new and emerging technologies, such as the WMO guidelines for conventional meteorological equipment. Clean and clear metadata is essential for the analysis of collected data and research transparency (Muller et al. 2013). This is a limitation of many urban climate studies (Stewart 2011). In this respect, citizen science–based data has the potential to fill gaps in knowledge and to optimize sensor network configuration.

## Data visualization

Visualization is an important part of workflow. Typical tasks include the analysis of the data and the communication of collected information to different audiences (Rautenhaus et al. 2018). With increased data size and underlying complexity, creating effective visualization becomes more challenging. Machine learning and data mining methods can bring complex datasets to higher abstraction levels so that they can be more easily interpreted (Wu et al. 2020). Rautenhaus et al. (2018) summarized historical and current visualization strategies for weather forecasting and meteorological research. Nocke et al. (2015) reviewed state-of-the-art climate network visualization and existing tools. Typical visualization of static results of climate networks included time series, global maps, scatter plots, or line plots (Nocke et al. 2015). Using interactive visualization, the power of the human visual system, and the strengths of computer-based data analysis can be exploited further (Nocke et al. 2015; Wu et al. 2020). In this regard, visual analytics offers an extensive body of knowledge about visualization and interaction techniques that could be adopted in biometeorological research. This can enable the user to find additional value in the data set. Challenges regarding frequent usage of interactive visualization lie in the time dependency, uncertainty in data attributes, and filtering settings. Time dependency adds an additional dimension to the data that often needs to be loaded separately, which can hinder the exploration of temporal trends in large data. Another challenge in interactive visualization is the uncertainty of data structure and its attributes. In addition, filtering settings may render the results arbitrary since they are usually not derived from quantitative criteria (Nocke et al. 2015). Virtual reality can offer some advantages for biometeorology. Caluya and Santos (2019) for example developed a virtual reality tool utilizing a 360° camera to train weather observers based on previous human observation examples.

### Cross-cutting and integrated scientific approaches

The impacts of climate change on society are cross-cutting and integrated scientific approaches are needed to address the multi-faceted challenges presented by climate change and extreme weather. Scientific studies often investigate a single parameter (or variable) and do not examine a problem in its entirety. Many research programs face resource challenges where budgets may be cut or reduced. This necessitates building synergies across disciplines to maximize the usage of existing personnel and infrastructure (Gruntfest 2018). Integration across disciplinary silos can change the approaches used to solve scientific problems rather than letting technology or disciplinary specializations determine and drive which problems are addressed (Whitesides 2014). Open Science (including open hardware and software) is a prerequisite for cross-silo integration and it can support a more equitable, inclusive, and accessible knowledge commons and infrastructure (Traynor and Foster 2017). Complex digital solutions fed by IoT connected sensors and complemented by crowdsourced data help to merge this gap, by providing a means to merge interdisciplinary information in a single analysis and/or visualization platform. Digital twin cities are examples of such endeavors but the concept of digital twin itself can be applied for any scale and subject. Biometeorological research is interdisciplinary by its very nature. Advancements in measurement and sensing technologies enable researchers from different backgrounds to work across disciplines and address the shared challenges posed by climate change and extreme weather events.

## Conclusions

Advancements in sensing technologies provide a plethora of meteorological and biological data across scales. Innovations in information and communication technologies have also led to dramatic improvements in the dissemination of data across jurisdictions and disciplines. Such unprecedented growth provides a unique opportunity to advance biometeorological research, especially in relation to studies that analyze how weather and our changing climate influence the health of humans, animals, and plants. Understanding the opportunities and limitations presented by current and emerging sensing technologies is foundational for the advancement of biometeorological research and a more sustainable and healthy future.

**Acknowledgments** The authors would like to acknowledge that the hypothesis for this manuscript was developed at the 3rd international workshop of the International Society of Biometeorology's Students and New Professionals (SNP) commission group. This SNP workshop was held in Enschede, the Netherlands, in December 2019. Special thanks to Prof. Pablo Fernandez for his participation at the SNP workshop and his mentorship and insight into the discipline. Funding for this workshop was provided by a grant from the International Society of Biometeorology and the S. W. Tromp Foundation. The contributions of Hamed Mehdipoor and Raul Zurita-Milla were supported by the Make It Sense program of the University of Twente.

**Authors' contributions** All authors contributed to the study conception and design. Material preparation and data collection and analysis were performed by all authors. The first draft of the manuscript was written by Vidya Anderson, Andrew Leung, and Hamed Mehdipoor and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

**Data availability** Not applicable.

### Compliance with ethical standards

**Conflict of interest** The authors declare that there are no conflicts of interest.

**Code availability** Not applicable.

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