CHAPTER 11

Environmental Monitoring for Health and Wellness

Our environment plays a pivotal daily role in our health and well-being. The air we breathe, the water we drink, the noise levels we're exposed to, and the weather we experience, all directly affect us in terms of our quality of life, our life expectancy, and the prevalence of certain diseases or other aspects of our personal health.

Poor air quality, for example, has been linked to premature death, cancer, and respiratory conditions such as chronic obstructive pulmonary disease (COPD). Second-hand smoke from cigarettes has been correlated with lung cancers and other respiratory conditions among non-smokers (Barnoya et al., 2005, Sasco et al., 2004). Pesticide contamination in the environment has been linked to a drop in male fertility (Bretveld et al., 2007, Balabanic et al., 2011). Global industrialization, urbanization, transport systems, agriculture, and energy production—all driven by population growth— are putting an enormous strain on our environment.

If current human societal behavior continues unchecked, we will need to consume more resources to drive our energy-hungry lifestyles, resulting in increased levels of pollution— including greenhouse gases, as shown in Figure 11-1. The Global Burden of Disease study estimates that 24 percent of the world's burden of disease can be attributed to environmental factors (IHME, 2013). The report attributes 3.2 million adult deaths globally to ambient air pollution in 2010, up from 2.9 million in 1990. In addition, 3.5 million adult deaths were associated with household air pollution exposure, such as indoor smoke from solid fuels. The report points out that the total number of deaths related to air pollution (6.9 million) exceeded those attributed to cigarette smoking (6.3 million). However, when dealing with such estimates, the contribution of modifiable risks factors also needs to be considered. For example, how many of the individuals were cigarette smokers or had occupations that increased their risks, as opposed to individuals who were unavoidably exposed to air pollution? Personal sensing in the future may offer quantifiable insights at an individual level into the amount of avoidable and unavoidable air pollution we are exposed to.

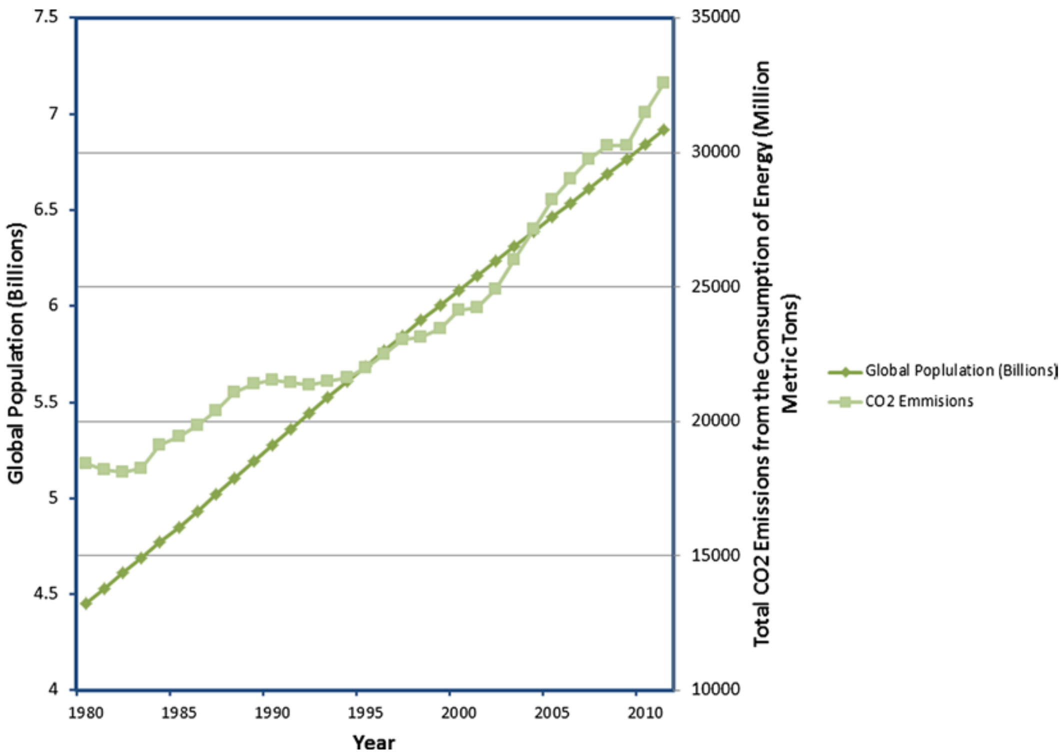


Figure 11-1. *Growth in global population and rise in carbon dioxide (CO_2) emissions due to energy consumption (Sources: US Energy Information Administration, US Bureau of the Census)*

Environmental monitoring focuses primarily on the identification and measurement of pollutants in the form of chemical, biological, microbiological, and radiological containments in water, soil, and air. In addition, ambient environmental monitoring targets variables such as temperature, humidity, and noise levels. While monitoring has been used for many decades, approaches to date have relied mainly on in-situ representative sampling (grab sampling), followed by laboratory analysis of samples. While highly accurate, this is slow, laborious, intensive, and not scalable. From a regulatory perspective, there has been significant interest in the use of sensing technologies, which can extend the capabilities of the laboratory to sites of interest. Some successes have been achieved, particularly with air-quality monitoring. However, these sensors cost tens of thousands of dollars, which limits their scalability and restricts their use to a small number of static sites within a given area.

Because of the need for improved, affordable and scalable sensing, there is growing interest in the use of lower-cost wireless sensors for environmental monitoring applications, both in the regulatory and non-regulatory domains. Moreover, individuals who have become increasingly aware of their ambient environment are interested in monitoring the quality of that environment. This is driven in part by extending the concept of the quantified self to embrace environmental influences. The ubiquitous nature of smartphones and tablets is also enabling the development of early-stage crowdsourced sensing capabilities in which citizens become mobile sensors of their own environment.

■ **Quantified Self** A movement of individuals who are interested in using sensors and other computing technologies to track on a daily basis a variety of data about themselves, such as what they eat, the quality of their ambient environment, their physical activities and performance, and other key health metrics in order to better understand their health and well-being (QS, 2012).

Environmental monitoring can generally be categorized into indoor and outdoor applications. Indoor applications typically focus on home, workplace, and office environments. Quantities of interest measured using sensors include temperature, humidity, light levels, air quality, and noise. Other measurands of interest from a safety perspective include smoke and carbon monoxide (CO) (see Chapter 10). Outdoor monitoring involves a wide variety of scenarios, including air pollution, water quality, traffic noise, weather, geological events such as earthquakes and volcanic eruptions, and agricultural applications that monitor, for example, soil moisture levels. In this chapter we focus on environmental sensing as it relates to human health and well-being.

Drivers of Environmental Sensing

A number of technical, social, and economic drivers are influencing the growing interest and adoption of sensors for environmental monitoring applications. As the cost of sensors decreases and their accuracy grows, they are becoming more viable platforms for in-situ monitoring applications. In addition, flexibility in their form factor enables protocol innovation and supports sampling regimes, which would be impossible or prohibitively expensive using traditional approaches.

Cost

The current approaches to environmental monitoring use high-cost analytical instrumentation for either in-situ monitoring or online analysis in laboratories. While these techniques, such as gas chromatography and mass spectroscopy, are accurate and offer appropriate sensitivity, they range in cost from thousands to tens of thousands of dollars. In contrast, sensors costing tens or low hundreds of dollars based on semiconductor, optical, and electrochemical techniques are becoming available. These devices can be incorporated into discrete, autonomous platforms, which can form the basis of distributed wireless sensor networks. With careful calibration strategies, these sensors can serve as low-cost alternatives to centralized instrumental monitoring for certain applications. The increasingly lower price point is enabling a rapidly developing market for personal environmental products, such as AirQualityEgg, which runs between $100 and $200.

Smartphones

The widespread adoption of smartphones is providing both a low-cost environmental sensor-aggregation platform and, in some cases, the actual sensing platform. For example, applications that track ambient noise can use the microphone integrated in every smartphone. The built-in GPS functionality can be used to geotag data, which is particularly important for mobile crowdsourced applications. Data shared via e-mail, SMS, or the Web can be a particularly useful for local environmental monitoring agencies. Smartphones provide a single form factor for all data-related processes, and their use will continue to grow in both professional and citizen-centric applications, particularly as more wireless-enabled environmental sensors become available.

Civic Sensing

As sensor technologies for environmental monitoring become more widely available and affordable, interest among individuals in monitoring their environment will grow. Active involvement in the generation and consumption of environmental data changes perceptions, attitudes, behaviors, and the level of engagement. Concerns are driven by frequent media reports of issues with air quality, drinking water, and food contamination, coupled with visible signs of problems, such as smog in many large cities. Individuals may be worried about exposure to environmental contaminants during outdoor exercise, such as running or jogging, particularly in urban environments. Parents may have concerns about the impact of pollution on a child or other family member, such as an elderly parent whose health makes them sensitive to environmental factors. The data is often seen as being complementary to personal health and wellness initiatives, as outlined in Chapters 9 and 10. Increasingly, society is focusing on creating a better understanding of cause-and-effect relationships between health and the environment, based on sharing data among online communities.

Sampling

Environmental monitoring often relies on the use of in-situ sampling, sometimes referred to as grab sampling. These samples are collected in labeled sample containers or gas bags and then stored under environmentally controlled conditions for transport back to the laboratory for analysis. The approach is slow, costly, and may even be unrepresentative of the quantities of interest, particularly in dynamic environments where pollutants may be transient. Delayed detection of issues can also have public health implications. For example, in epidemics, members of the public inevitably become ill before the problem is identified more broadly. The use of sensor-based approaches can help to address these limitations and facilitate earlier detection of contaminants and pollutants. However, the sensors may need to be coupled with automated sampling systems to ensure that they are exposed to consistent and reproducible samples.

Environmental Sensing and Network and Communications Technologies

Many environmental sensors have wireless capabilities ranging from low-power Zigbee to Wi-Fi or 3G/4G communications. Zigbee-based nodes can be deployed in a mesh network configuration using multihop protocols to cover larger geographical areas than can be covered using a standard star topology. Wi-Fi offers outdoor ranges of 100 to 200 meters (about 300-600 feet), while 3G and 4G both have significantly longer ranges. This allows the sensors to be deployed over larger geographical areas, a frequent requirement for environmental applications. However, it is important to ensure that, from an economical perspective, the density of deployment required for effective communications is appropriate. There is often a trade-off to be made between building a network with a small number of high-power devices, and using a larger number of low-power devices with sufficient overlap in their communication fields to ensure reliable communications (Linear-Technology, 2012, Ghosh et al., 2008). There is growing support for IPv6 on sensor nodes to provide IP end-to-end connectivity (see Chapter 4). Use of this protocol simplifies the process of connecting wireless sensor network (WSN) devices to the Internet and helps to realize the paradigm of the Internet of Things (Mainwaring et al., 2010).

Making the data generally available online will enable environmentally aware hacktivists to easily create web-based applications and mobile apps that can be used to inform and educate the general public. The use of IPv6-based protocols also allows system designers and users to leverage the rich ecosystems of tools that have already been developed for commissioning, configuring, and administering these networks.

■ **Hacktivists** Those who use computers, the Internet, social media, and other digital tools to promote a political or ideological cause. Hacktivism incorporates a broad range of activities that often operate just within the boundaries of legality by exploiting the concept of freedom of speech (Conway, 2012). However, some consider that certain activities cross the threshold of legality. Environmental hacktivists can use sensor technologies to collect data in order to promote a specific cause, or to highlight a specific issue. Their intention is typically to raise public awareness in an effort to put pressure on politicians to implement policy changes that are beneficial to the environment. However, the ability of environmental hacktivists to interpret the data correctly is subject to some debate. Some argue that they may cause unnecessary panic and misinform the public. How we educate the public to deal with such campaigns will grow in importance. In a data-driven society, individuals need to have a greater understanding of scientific data in order to make their own interpretations. Understanding and a skeptical mind are required for stimulating informed criticism, which ensures that suppositions and hypothesis are adequately tested and debated and not simply accepted as fact.

Barriers to Adoption

Despite the potential of sensor-based monitoring, both from a regulatory and a citizen perspective, many barriers remain to be overcome before widespread adoption is truly possible. These include power consumption, robustness and cost, available sensor technologies, security, usability, scalability, and interoperability. Let us examine these factors in more detail.

Power Consumption

Power consumption remains an operational constraint, particularly for remotely deployed applications where it is not possible to provide access to AC power. Even when AC power is an option, the cost of provisioning connections is usually expensive. Energy-harvesting options, such as solar panels, are available; however, they can be expensive relative to the cost of the sensor. The return on investment can be on the order of years, which may be longer than the planned lifetime of the deployment. Maintenance overhead is also a consideration that adds cost to the system deployment (Zervous, 2013). Panel size can be issue in term of power output; that is, panel sizes may have to be large to generate sufficient power for some system configuration, such as embedded computing data aggregators. (See Chapter 4.) Large panel sizes may not be an option, depending on the location of the deployment. Sensor-node deployments with battery-power sources are still the most popular. Sensor-node lifetimes typically exhibit a strong dependency on battery life. Improvements in battery technologies and the use of energy-harvesting techniques, such as solar panels and micro wind turbines, have increased the available energy budget. However, careful design of sensor networks is generally required to minimize compromises in duty cycle and measurement frequencies.

Robustness and Cost

Many environmental applications expose sensors to harsh conditions. The sensors, batteries, and other sensitive electronic equipment need to be protected from rain, ice, dust, and other sources of contaminants. The enclosures will typically have an Ingress Protection Rating (IPR). The IPR specification (see Table 11-1) is published by the International Electrotechnical Commission (IEC) within the IEC 60529 standard. The IPR rating for an electronic device typically consists of the letters IP, followed by a two-digit number, such as IP65, which indicates complete protection, limited ingress permitted. The first digit identifies the protection against intrusion of solid objects, such as human or tool contact or foreign bodies, such as dust. The second digit in the IP rating identifies the level of protection again moisture ingress. For environmental applications, this ranges from 6 to 8. In the United States, the National Electrical Manufacturers Association (NEMA) publishes protection ratings for enclosures that are similar to the IP ratings. It differs from the IPR specification in that it dictates other product features, such as corrosion resistance, gasket aging, and construction practices.

Table 11-1. *Ingress Protection Rating Codes*

	First Digit			Second Digit	
	Protection against Human/Tool Contact	**Protection against solid objects**		**Protection against water**	**Protection against condition**
0	No special protection	No protection	0	No protection	
1	Back of hand, fist	Protection against a solid object >50mm	1	Protected against vertically dripping water	Condensation, light rain
2	Finger or similar objects	Protection against a solid object >12mm	2	Protected against vertically dripping water when tilted 15 degrees	Light rain with wind
3	Tools and wires etc. with a thickness > 2.5mm	Protection against a solid object >2.5mm	3	Protected against water spraying at an angle up to 60 degrees	Heavy rainstorm
4	Tool and wires etc. with a thickness >1mm	Protection against a solid object >1mm	4	Protected against water splashing from any direction	Splashing
5	Complete protection (limited ingress permitted)	Dust protected	5	Protected against jets of water from any direction	Hose down, residential
6	Complete protection	Dust proof	6	Protected against powerful jets of water from any direction	Hose down, commercial
			7	Protected against immersion between a depth of 150mm and 1000mm	Immersion in tank
			8	Protected against submersion—depth specified by manufacturer.	Immersion > 1M

Sensors can be purchased with casings that have high IPRs or, especially when a deployment requires multiple sensors, they can be mounted in an IPR cabinet enclosure. The cost of enclosures meeting these specifications can be relatively high, often more than the sensors themselves. For example, a small IP-67 all-weather plastic enclosure (150mm x150mm) will cost in the region of $100 to $200. There is growing interest in the use of 3D printers to create low-cost enclosures that can be produced at a fraction of the cost of injection molded plastics (Boisvert, 2013). However, the technology needs to mature further to meet the rigorous demands of environmental applications.

While the cost of some environmental sensors is becoming affordable for use by consumers, the cost of institution-led deployments (by academic and regulatory bodies) remains high if not prohibitive. The actual sensor cost may represent a fraction of the overall deployment cost, which includes enclosures, aggregators, communications installation, as well as ongoing administration and maintenance costs. New system-on-chip (SOC) components are emerging, particularly for M2M (machine-to-machine) applications, which will help to reduce some of these deployment costs. However, it is likely to take a number of years for these components to feed into the sensor ecosystem. Moreover, the ability to produce low-cost, sensitive, and reliable sensors remains a challenge. But the proliferation of smartphones can provide a zero-cost platform for the acquisition, processing, presentation, and archiving of disposable sensor data, which greatly simplifies sensor requirements (Crisostomo, 2013, Sensorcon, 2013).

Technology Limitations

The capabilities and sensitivity of low-cost sensors remain somewhat limited. Currently, environmental monitoring usually uses a restricted range sensors types, such as those for temperature, light, humidity, and atmospheric pressure, which might found in a hobbyist weather station. While low-cost semiconductor and electrochemical gas sensors and particulate matter (PM) monitoring sensors are available, their sensitivity and accuracy are often inferior to current instrumental techniques (Choi et al., 2009); (Romain et al., 2010). Careful and continuous calibration protocols can improve the performance of some sensors, but significant progress remains to be made. The use of sensors to detect bacterial contamination in water is one of many areas of active research (Grossi et al., 2013). Sensors to detect pathogens such as E. coli have been demonstrated (Mannoor et al., 2010). However, the availability of commercial sensor technologies is still extremely limited. It will likely be a number of years before sensor technologies for in-situ detection of bacterial contamination for real-world applications emerge.

Security Concerns

The security of sensors for institutional applications remains a cause for concern. Data that identifies particular threats to public health often results in preventative or remedial actions by public officials, which can have significant social and economic impacts. It is therefore critical that the data used to initiate such actions has appropriate integrity. Highly robust security generally requires significant computational capabilities to implement correctly, which is difficult to achieve on energy-constrained sensors. Progress continues, but the challenges of implementing scalable, robust, security systems for low-computational sensor devices are significant. The emergence of low-cost M2M SOCs with integrated software and hardware security features may offer some relief in the medium term.

Usability and Scalability

The usability of sensors and their supporting software can be challenging, particularly for the hobbyist user who buys them off the shelf. The development of firmware remains outside the technical capabilities of most potential users. It is therefore important that both discrete and wireless sensors become easier to install, maintain, and understand. Ideally, the sensors need to evolve into plug-and-play operability. And they need to be easily discoverable by aggregators such as smartphones, with highly intuitive support apps and simple connectivity to cloud services for sharing, aggregation, and analysis.

WSNs for environmental monitoring, scaled to thousands of nodes over large geographical areas and operating successfully for years, have yet to be achieved. To date, WSNs have been demonstrated for environmental proposes but have been limited to double-digit or low hundreds of sensor nodes (the term node or sensor node is used to describe a sensor that is part of a larger network and is capable of connecting to the other nodes in the network to exchange data and other messages). It remains to be demonstrated that the available theoretical solutions reported in the literature are suited to large WSNs supporting real-world environmental applications.

Interoperability

The interoperability of sensors from different vendors is a major challenge for market participants. Sensors are available with a variety of standards-based or proprietary communications protocols. Even when standards-based radios are used, the firmware usually implements a custom data payload that varies from vendor to vendor. Wireless communication technology can be successful only if the sensors of different vendors can communicate successfully. Such a multivendor interoperability environment is expected to be a long-term challenge.

Data Quality and Ownership

As sensors become more widely available and deployed, the granularity and pervasiveness of monitoring will increase. The concomitant increase in data will most likely generate significant discussion and debate. Key among the questions that will have to be answered are as follows:

- Whose data is it?
- How should it be interpreted?
- How do we ensure data quality?
- Does crowdsourced data have appropriate statistical significance?

These questions and many others will likely fuel debates between environmentally concerned citizens and vested interests in the form of commercial, public, and government entities and environmental activists. The debates will center on the validity and meaning of the data and the potential actions to be taken to improve the health and wellness of citizens.

Environmental Parameters

Environmental monitoring has generally focused on the detection and measurement of contaminant concentrations and identifying when contaminants have dissipated to levels that no longer pose a public health risk. Monitoring approaches assess the chemical, physical, radiological, and biological properties of a medium under test, such as air or water. Longitudinal monitoring in a particular location is used to establish normative ranges and identify results that fall outside these ranges. More recently, the focus area of environmental monitoring has expanded beyond contamination detection to include noise pollution, solar radiation levels, and ambient urban conditions.

Air Quality and Atmospheric Conditions

Air quality receives frequent attention in the media in relation to topics such as the burning of fossil fuels, global urbanization, the proliferation of cars, intensive agriculture and industrial pollution. Human activity is having an impact on air quality in many parts of the world. One of the most visible manifestations of this is photochemical smog, comprising pollutants such as nitrogen oxides and dioxides, volatile organic compounds, ozone, and aldehydes. Smog is a global problem affecting cities such as Los Angeles, Beijing, and Mexico City. Figure 11-2 shows the annual mean of PM_{10} (particles with a diameter of 10 micrometers or less) in cities by region from 2003 to 2010. Clearly, many regions across the globe are exceeding what are considered to be safe limits for various forms of pollutants, including airborne particulate matter.

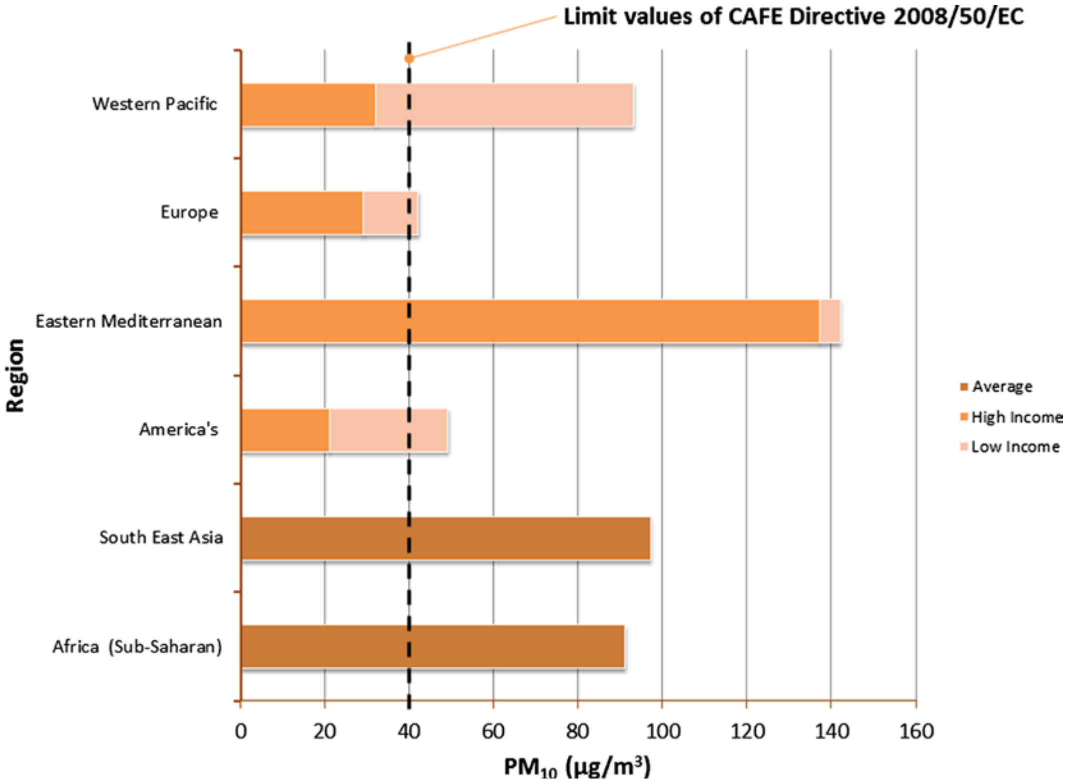


Figure 11-2. *Annual mean of PM_{10} in cities by region from 2003 to 2010 (source: WHO)*

Air quality and its components are generally defined by national legislation such as the Clean Air Act in the U.S., and in Europe by EU ambient-air legislation, such as the Ambient Air Quality and Cleaner Air for Europe (CAFE) Directive (2008/50/EC); see Chapter 7 for further details. Legislation defines both qualities of interest and their limits, and how they should be assessed and managed by national agencies.

The technique used depends on the pollutant of interest. O_3 (ozone), for example, is measured using ultraviolet (UV) absorption, whereas fluorescence spectroscopy can be used for the detection of inorganic compounds such as SO_2 (sulphur dioxide) (Queensland Government, 2011). In the U.S., fixed monitoring stations are augmented with self-contained mobile laboratories called Trace Atmospheric Gas Analyzers (TAGA). The TAGA bus can be deployed to monitor air quality and other measures of interest during or after exceptional events—such as the BP spill in the Gulf of Mexico—to determine risks to public health. From an air-quality perspective, the EPA focused on measuring concentrations of volatile organic chemicals (VOCs) from the oil spill and chemicals used in the oil-dispersant process, both of which had vaporized into the air (EPA, 2010). All instruments used for institutional air-quality measurements must meet the required standards, such as EN12341, the EU specification for the performance of PM_{10} sampling instruments (Standards, 1998), and 73 FR 66964, the U.S. national ambient air-quality standard (NAAQS) for lead (EPA, 2008). Strict guidelines also cover the calibration of the instrumentation, sampling methodologies, and so on. Collectively, this makes ambient air quality monitoring specialized, inflexible, expensive (with instruments ranging from thousands to tens of thousands of dollars), and not very scalable across large geographical areas. As a result, there is growing interest in the use of lower-cost, discrete, wireless sensor networks to augment regulatory air quality monitoring.

Monitoring air quality entails measuring a wide variety of parameters at different levels of sensitivity across different timeframes, which can be difficult for the public to consume and interpret to their satisfaction. To address this issue, government agencies often use an air-quality index for health (AQIH). This number expresses complex air-quality information in simple terms to inform the public of the current air pollution level and its potential impact on their health. Such indices are particularly important for sensitive groups, such as asthmatics. In Ireland, the AQIH is a ten-point range, divided as follows (EPA, 2013):

- Good (1-3)
- Fair (4-6)
- Poor (7-9)
- Very poor (10)

The index is based on five parameters: the one-hour average of SO_2, NO_2 (nitrogen dioxide), and O_3, combined with a rolling 24-hour average of PM_{10} and $PM_{2.5}$ (particulate matter with a diameter less than 2.5 microns). The overall AQIH is the highest of the five pollutant indices. In the U.S., the air-quality index is defined by the EPA. The AQI comprises six categories correlated with increasing impact on health, as shown in Table 11-2. Values over 300 indicate hazardous air quality, while values below 50 are considered good (EPA, 2013).

Table 11-2. *EPA Air Quality Index Based on Five Pollutants Regulated by the Clean Air Act (ground-level 0_3, particulate matter, CO, $S0_2$, and $N0_2$); (source: U.S. EPA)*

Air Quality Index (AQI)	Levels of Health Concern	Definition
0-50	Good	Air quality is satisfactory.
51-100	Moderate	Air quality is acceptable. Some pollutants may be at a level to be of moderate concern for a very small number of individuals who are sensitive to air pollution.
101-150	Unhealthy for sensitive groups	Members of sensitive groups may experience health effects. The general public is unlikely to be affected.
151-200	Unhealthy	Most people are likely to experience health effects.
201-300	Very unhealthy	Health warnings to indicate emergency conditions.
301-500	Hazardous	Health alert—everyone is at risk for serious health effects.

In addition to air-quality measurements using sensors and analytical instrumentation, satellite monitoring has been used for many years. A key advantage of a satellite-based approach is its ability to cover a large geographical area, which can be useful in identifying and tracking sources of pollution. A number of instrumental techniques are employed for measuring pollutants. For example, the GOME-2, launched in 2006, is a European instrument carried on the MetOp-A satellite. GOME-2 uses a scanning spectrometer that captures light reflected from the Earth's surface and atmosphere. The spectrometer splits the light into its spectral components to map concentrations of atmospheric 0_3 as well as $N0_2$, SO_2, other trace gases, and ultraviolet radiation (see Figure 11-3). Data from the GOME-2 instrument provides insights into atmospheric composition and levels of pollutants (WDC-RSAT, 2103). Data from NASA's Earth Observatory satellite Terra has recently been used to show $PM_{2.5}$ pollution over Beijing in China. The satellite images were in used in conjunction with ground-level sensing at the U.S. embassy in Beijing, which recorded $PM_{2.5}$ measurements of 291. The World Health Organization specifies that $PM_{2.5}$ levels above 25 are considered unsafe (CBS, 2013). Scientists are becoming interested in combining satellite measurements of $PM_{2.5}$ with ground-based measurements, and there are calls within the scientific community for air-quality and space scientists to work together more closely on $PM_{2.5}$ and other forms of pollution monitoring (Hidy et al., 2009).

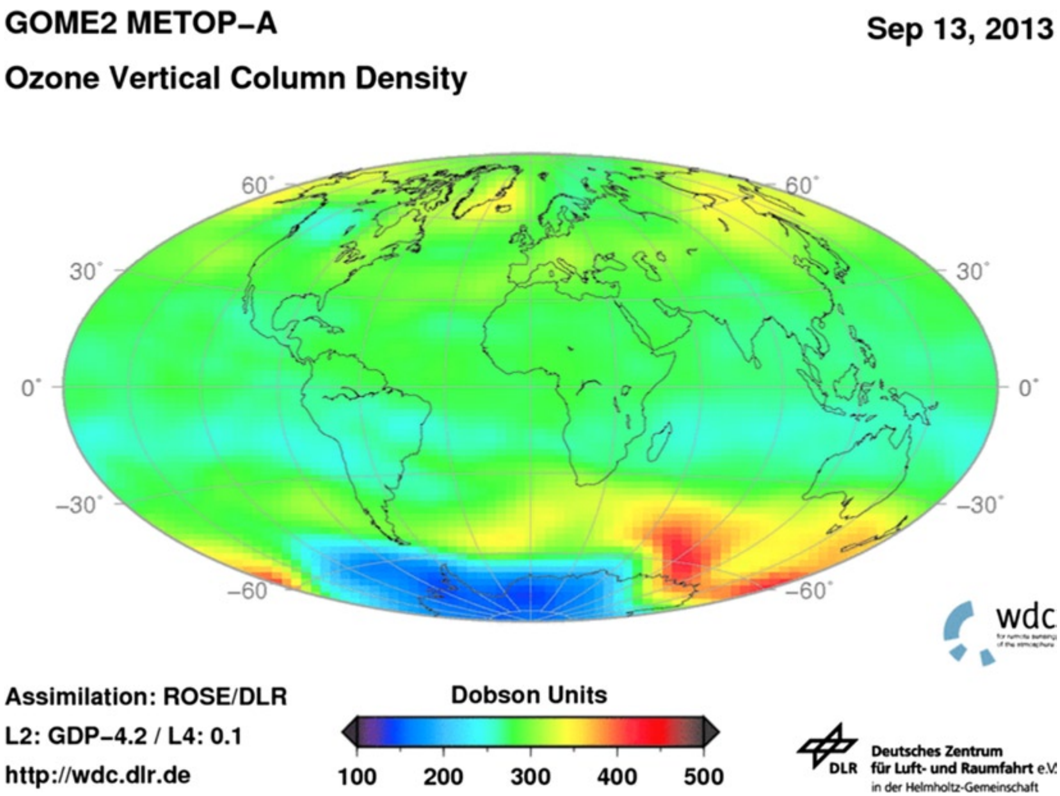


Figure 11-3. *Global ozone levels measured by GOME-2 (image source: the ICSU World Data Center for Remote Sensing of the Atmosphere)*

Satellite observations also play an important role in monitoring global temperatures. Temperature measurements are made indirectly by measuring radiances (the quantity of radiation that passes through or is emitted from a surface at a given angle in a specific direction) in various wavelength bands, which are then mathematically converted into temperature measurements. Various methods exist for the conversion of the radiance measurements into temperature. Differences in the results obtained from these methods have led to some debate, especially because the data is an important input into global temperature models. Groups such as the Remote Sensing Systems (RSS) and the University of Alabama in Huntsville (UAH) play an active role in calculating temperature measurements from satellite observation (MedLibrary.org, 2013).

Sensing Air Quality

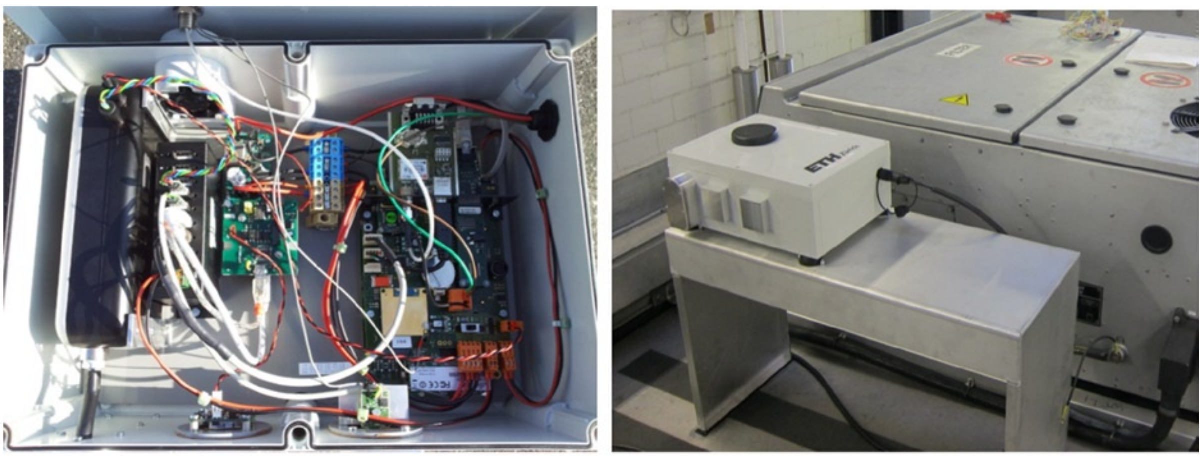
The use of low-cost sensors to generate air quality data that is then made available online for public consumption has been gaining in popularity. These data sets can be used to support local initiatives, such as driving changes to local government policies. They can also be used for personal applications, for example, to improve asthma management. Keep in mind, however, that these data sets will often have limitations due to data-quality issues. Low-cost sensors, particularly semiconductor-based ones, may not have the required level of sensitivity. They may also exhibit drift without appropriate calibration procedures. The performance of the sensor may be influenced by the ambient conditions such as temperature. It is therefore important to select sensors with an appropriate level of sensitivity and linear range for the given use case. The deployment strategy, enclosures, sampling methodology, and so on must be carefully chosen to minimize any impacts on performance within the required operational envelope.

A variety of wireless sensor deployments to monitor air quality and corresponding weather conditions, particularly in urban locations, have been reported in the literature over recent years. One such deployment in Taipei, Taiwan monitors CO emissions from vehicular traffic. The system consists of sensor nodes, a gateway, and a back-end platform controlled by a LabVIEW program through which sensing data was stored in a database. The deployment consisted of nine sensor installations with Global System for Mobile Communication (GSM) connectivity. Two CO peaks were found, at 7 a.m. and 7 p.m., corresponding to rush-hour traffic. Moreover, high concentrations of pollutants were detected that continued accumulating when motor vehicles waited for red lights. Some sensor nodes detected CO concentrations of up to 9 parts per million (ppm)—above the limit recommended for long-term human exposure (Jen-Hao et al., 2011).

Other efforts include the CitySense platform deployed at Harvard University and the surrounding area to monitor a number of air-quality parameters, including PM_{10}, CO_2, NO (nitrogen oxide), and O_3. These measurements were augmented with weather and ambient-noise data. Visualization of the data was achieved using Microsoft's SensorMap platform (Murty et al., 2008). A similar deployment was carried out in New York City, where mote-based sensors were used to measure humidity, temperature, atmospheric pressure, barometric pressure, and light levels. To add context to the sensor data, a geographic information system (GIS) implementation provided a geographic overlay for understanding the sensor locations. Each node was identified by name, tag, and current measurements at the nodes location (Morreale et al., 2010).

A key enabling feature of wireless sensors is supporting mobile applications, which give them an advantage over static monitoring stations that are tied to a specific location. This capability has been used in air-quality monitoring deployments in cities such as Cape Town, South Africa. In that deployment, Waspmotes (an extensible wireless sensor platform with sensor boards for environmental, agricultural, smart cities, and radiation monitoring), with gas sensor boards from the Spanish company Libelium, were used in a car following predefined routes to map the pollution levels in the city. The data was presented as a proof of concept—a first step in realizing a vision of how cars with cloud connectivity and integrated sensors could act as mobile, real-time air-monitoring stations (Bagula et al., 2012).

Transport-enabled sensing has been effectively demonstrated by researchers from ETH Zurich using the public tram system in Zurich. Their air-quality project, OpenSense, monitors four primary pollutants O_3, CO, NO_2 and particulate matter (Li et al., 2012). All sensors are housed in a self-contained measurement station, as shown in Figure 11-4 (a). The core of the prototype station is a Gumstix embedded computer running Linux. The station supports General Packet Radio Service/Universal Mobile Telecommunications System (GPRS/UMTS) and wireless local area networks (WLANs) for communication and data transfer. A GPS receiver supplies the station with precise geospatial information. The measurement station is equipped with an accelerometer and, once installed on a tram, receives the door release signal to assist in recognizing tram stops to minimize positioning uncertainty. The station is supplied with power from the tram, as shown in Figure 11-4 (b).



(a) (b)

Figure 11-4. *(a) ETH OpenSense sensor station (b) Installation of an OpenSense measurement station on top of a VBZ cobra tram (image used with permission from Computer Engineering and Networks Laboratory (TIK), ETH Zurich)*

There are five stations on top of trams in Zurich and one at the national air pollution monitoring network (NABEL) station in Dübendorf. The performance of ETH's sensors can be compared with the EMPA's (EMPA, 2013) fixed environmental monitoring station. Reference data obtained by this station is used to calibrate the mobile sensors and to evaluate their performance under a wide range of weather conditions. The data is made public and can be accessed online at `http://data.opensense.ethz.ch`. It can be used to model how the various sensor parameters vary over the course of the year. For example, Figure 11-5 shows the variation in ultrafine particulate concentrations between spring and winter (Hasenfratz et al., 2012, Keller et al., 2012).

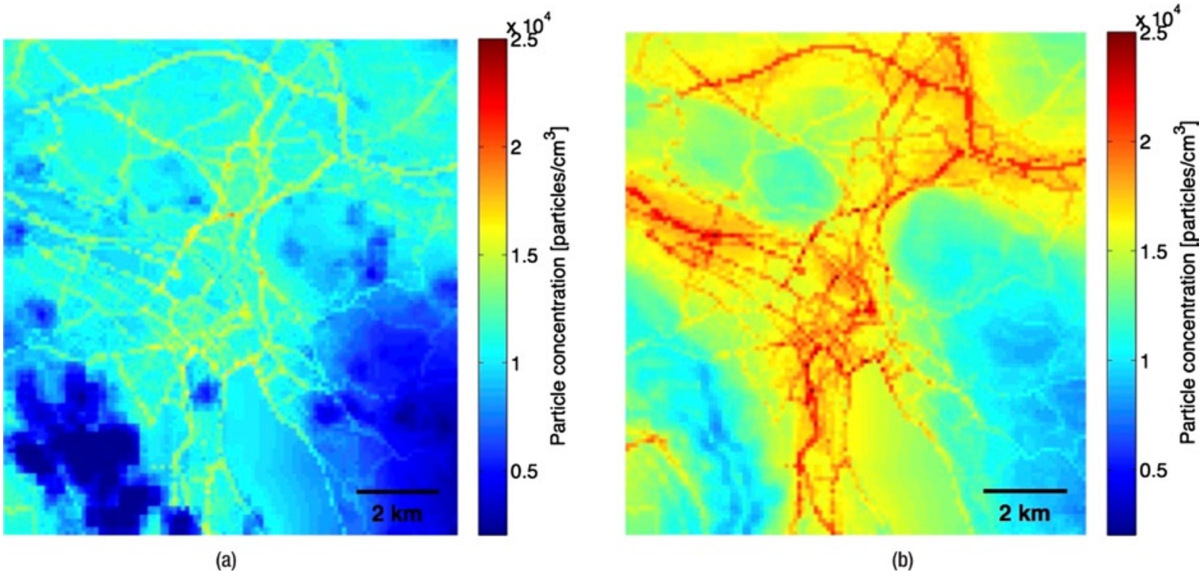


Figure 11-5. *Modeled ultrafine particle concentrations for Zurich during spring (a) and winter (b) (image used with permission from Computer Engineering and Networks Laboratory (TIK), ETH Zurich)*

In the commercial domain, AirBase Systems (`www.myairbase.com`), an Israeli start-up, has developed a low-cost, easy-to-use air quality sensor unit for indoor and outdoor monitoring applications, as shown in Figure 11-6(a) . The system is currently equipped to measure levels of O_3, NO_2, total VOC, total suspended particles (TSP), noise, relative humidity, and temperature. Other sensors can be added to monitor odor, light, and SO_2. The units require external power and feature both Wi-Fi and GSM communications. Once the sensor is powered up, data is available on a 20-second duty cycle. Any deviation from the allowed (or input) exposure standard generates an alert. Data from deployed stations can be made available on Google Maps to provide a live global view of air quality with drill-down into the data from each station, as shown in Figure 11-6(b)

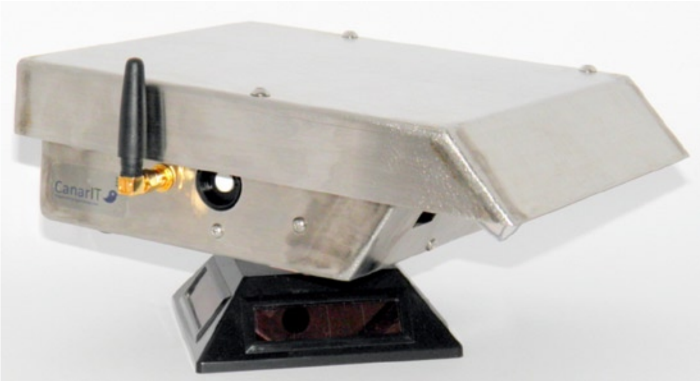


Figure 11-6a. *Outdoor CanarIT air monitoring from AirBase Systems (image used with permission from AirBase Ltd)*

Figure 11-6b. *Global representation of real-time data from CanarIT air quality monitoring stations (image used with permission from AirBase Ltd)*

Sensing Indoor Air Quality

The use of sensors in a home for a variety of applications is well-established. Chapter 9 reviewed how sensors have been used to deliver healthcare applications, and Chapter 10 looked at home safety and security applications. There is now a growing interest in developing applications that monitor the ambient environment in people's homes to enhance their comfort and wellness. One key focus area has been indoor air quality, which can negatively impact well-being. This interest is often driven by concerns about allergies or asthma, or the use of solid fuel heating stoves in a family living area. Poor air quality can result in symptoms often mistaken for colds, flu, or allergies: nausea, dizziness, headaches, breathing problems, eye irritation, and muscle pain. Common sources of indoor air pollution include carpeting and the adhesives used to install it, furniture fabric, and mold.

Kits are available that can collect air samples, which are then sent for laboratory analysis to identify problems, such as the presence of VOCs. The kits can be expensive and they provide only a snapshot in time of air quality. A number of sensors with smartphone connectivity, like the AQM-p from Esensors, are now available. They are aimed at the general public, and can provide continuous measurements of air quality inside or close to homes. One community-based initiative supported by a Kickstarter campaign that has received significant attention is the Air Quality Egg (airqualityegg.com). This sensor is designed to allow anyone to collect data on NO_2 and CO concentrations together with temperature and humidity. The sensor is placed outside the home to measure ambient gas concentrations and it streams the data wirelessly to an egg-shaped base station. The base station connects to a home broadband router via an Ethernet connection and sends data to the Xively web application, which visualizes and stores the data.

Another interesting sensor platform currently in beta testing is the AirBoxLab (www.airboxlab.com), which is actually a sensor array that measures VOCs, CO_2, CO, particulate matter, temperature, and relative humidity. Data from the sensor can be streamed to any computing device, including smartphones, for data access, and to the cloud for storage and additional processing. AirBoxLab is developing analytics capabilities, including pattern-recognition and machine-learning algorithms, that will enable proactive messaging designed to modify behavior to improve home air quality. That behavior might include air renewal by opening windows and doors in living spaces and locating sources of pollution to eradicate them.

A commercial product receiving significant media attention is Netatmo's personal weather station with air quality sensors, which monitors both indoor and outdoor air quality, weather, acoustic comfort, and other environmental parameters. The aesthetically pleasing aluminum enclosures (separate ones for indoor and outdoor use) are designed to be placed prominently in a living space, as shown in Figure 11-7. A key goal for the product is helping to improve people's wellness in their homes by informing them (via an iOS or Android app) when they should ventilate their living environment.

Figure 11-7. *The Netatmo personal weather station with air quality sensors (image used with permission from Netatmo, www.netatmo.com)*

This theme of wellness and improved quality of indoor living is also reflected in the recently launched CubeSensors product. These small, wireless sensors (50x50x50mm) continuously measure temperature, humidity, noise, light, air quality, and barometric pressure in any room in which they are deployed, and stream the data via the cloud to any computing device. The cloud service also sends alerts and recommendations to users on how to improve the indoor environment, including ventilation notifications, when to humidify or dehumidify, and so on. Launched in the summer of 2013, the initial batch of sensors sold out immediately.

For technically oriented environment enthusiasts, a number of kits have emerged, many based around the popular Arduinio platform. Arduinio kits based on a Sharp optical dust sensor are available for particle detection, for example. The sensor connects to an Arduinio shield via an Ethernet connection. Data can be sent to Xively for storage and visualization. In addition, Facebook and Twitter alerts can be received when new air quality sensor measurements become available (Nafis, 2012).

Researchers continue to actively develop and evaluate indoor environmental sensing platforms. Unsurprisingly, there is a particular focus on the use of smartphones for sensor data aggregation, processing, and remote transfer to cloud-based storage and processing. One example of this approach is the MAQS/M-Pod system developed by researchers at the University of Colorado at Boulder, which is designed to be body-worn on the upper arm or attached to a backpack. The M-Pods provide sensing for a standard range of air quality parameters. The system features a fan that pulls air through the sensor module. The fan is required to ensure that sensors are exposed sufficiently to the ambient atmosphere as they are housed within a plastic enclosure for protection. Data is streamed to a smartphone via Bluetooth. The system also features room location capabilities. The system leverages the smartphone's accelerometer to monitor the owner's entrance and departure. It triggers room localization via Wi-Fi RSSI (received signal strength indicator) room mappings only when a room entrance event is detected (Jiang et al., 2011).

The BodyTrack project at Carnegie Mellon University expands on smartphone-enabled monitoring by combining indoor air quality parameters with physiological sensing such as EKG/ECG, respiration and ambient parameters such as light and sound levels. The rationale behind this multisensory approach is to enable individuals to explore potential environment/health interactions. The influence of air quality on respiratory issues such as asthma or sleep problems can be investigated based on a cause and effect relationship. These relationships between data can be explored using an open source web service that allows users to aggregate, visualize, and analyze data from a variety of sources (Wright et al., 2012).

Community-Based Outdoor Air Quality Monitoring

For accurate and detailed information about the ambient air quality of a geographical area, covering the whole area with sensors is ideal. In practice, this is not feasible, so sensors are placed at desired locations, and useful information is constructed from the gathered data. With standard approaches, it can take a few years to collect and analyze the data for large-scale air-quality monitoring and generate detailed reports. This can be source of frustration for people dealing with air quality concerns such as odorous emissions from a local factory. To address this issue, community sensing is rapidly gaining attention. In this scheme, standalone mobile sensors or sensors integrated into wireless sensor networks capture data from the environment and share it on the Web. Discrete sensors can be paired with smartphones for data aggregation, processing, and sharing. The collected data can be further augmented by taking advantage of smartphone capabilities—for instance, geotagging the data using the built-in GPS. A key limitation of crowdsourcing is the potential variability in the quality of the sensor data. Issues can arise due to poor calibration of the sensors, unidentified degradation of sensor performance over time, use of poor sampling techniques, and more. As the popularity of this approach grows, initiatives will be required to address issues related to sensor calibration and data reliability, particularly if the data is necessary for informed decision-making.

The Common Sense project, which involved researchers from Carnegie Mellon and Intel Labs, deployed sensors onto a fleet of street sweepers in San Francisco (Aoki et al., 2008). Sensors for measuring CO, NO_x (oxides of nitrogen, for instance, NO and NO_2), O_3, temperature, relative humidity, and motion (using a 3D accelerometer) were connected to a mobile phone via Bluetooth. Location data was provided by the phone's integrated GPS. Data collected was sent to a database server via GSM text messages. The results from preliminary trials suggest the existence of microclimates (localized pockets with different mixtures of CO and NO_2) within sections of the city areas monitored by the Bay Area's air-quality agency. Eric Paulos, a researcher from Carnegie Mellon, argues that maintaining measurement stations across the city would cost millions of dollars and wouldn't deliver the kind of detail researchers can get from citizens' mobile phones with sensors costing as little as $60 each (Westly, 2009).

A similar approach called CitiSense was developed by researchers at the University of San Diego. They conducted a field trial with 30 users, each with a smartphone connected to an Amtel ATMEGA 128-based mobile sensor platform. The platform had sensors for temperature, humidity, barometric pressure, CO, NO_2 and O_3. An application running on the participant's smartphone displayed sensor readings using the EPA's color-coded scale for air quality (see Table 11-2).

Researchers were able to identify pollution hot spots along main roads, at traffic intersections, and at other places, which varied with the time of day. Participants in the study used the data to reduce their exposure to pollutants through personalized online maps. The maps were designed so that participants could visualize and explore their exposure data over the course of the study. People who cycled to the university modified their routes slightly to avoid busy streets with high levels of pollutants. Commuters who took the bus avoided waiting near the buses' exhaust (Zappi et al., 2012).

In Copenhagen, the public Wheel Project transforms ordinary bikes into hybrid e-bikes that function as mobile sensing units. Sensors were installed via a custom wheel hub onto the rear wheels of the bikes. Sensors measure ambient carbon monoxide, NO_x, noise, ambient temperature, and relative humidity as the bikes move through the city. Users place their smartphones on the handle bars, where data from the sensors streams via Bluetooth to the phone, which displays the data, allowing users to plan healthier bike routes. Users also have the option to share the data from their journeys online to build maps of city pollution levels (Wheel, 2013). Other platforms that report enabling community air-quality monitoring in local areas are P-Sense (Mendez et al., 2011) and the Citizen Sensor open source project (Saavedra, 2013).

While most efforts to date have used discrete sensors with smartphones to measure air quality, researchers at the University of Southern California have developed an Android app called Visibility, which uses the smartphone's camera to measure airborne particulate matter. User images of the sky are tagged with metadata such as location, orientation, and time. The data is then sent to a remote server for analysis, where the air quality is estimated by calibrating the images sent and comparing their intensity against an existing model of luminance in the sky. Once processing is complete, the result is sent back to the user. The data is also used to create pollution maps for the local geographical region (Ganapati, 2010).

Commercially available sensors have started to emerge to enable crowd-sourcing of environmental data, such as SensPods (Sensaris, 2013). Their compact wireless environmental measurement unit is designed for participatory sensing. They have sensing capabilities for a variety of parameters, including humidity, CO_2, temperature, CO, radiation, noise, NO_x, luminosity (UVA, UVB, UVC), GPS, O_3, and $PM_{2.5}$ or PM_{10}. The sensor modules can be integrated with either Android or iOS smartphones via Bluetooth. Data can also be sent to the Sensaris Sensdot web back end for intuitive visualization in a variety of graphs over user-defined time periods. The data can also be displayed on a geolocalized map (as shown in Figure 11-8) so users can develop a picture of the air quality in areas where they live or work.

Figure 11-8. *The Senaris SensPods system for mobile ambient environmental monitoring (image used with permission from Sensaris - www.sensaris.com)*

Monitoring Ambient Weather

Although ambient monitoring applications normally focus on air quality measurements, interest is emerging in using sensors to monitor the outdoor influence of weather on physiological well-being. As the manner in which we live becomes more urbanized, the built environment (particularly when combined with weather events such as heat waves) can have a significant influence on health and well-being through thermal stress. The heat-island effect associated with large cities is a well-documented phenomenon: temperatures can range from 1 to 10°C higher than surrounding rural areas. Typically satellite observations coupled with GIS systems have been used to monitor the effect. Previous generations of satellite instruments suffered from granularity constraints; however, the current generation of instruments has significantly improved spatial-resolution capabilities. Sensor deployments, either fixed or mobile, can provide highly granular data, capturing the impact of local influences. This kind of detail at ground level complements satellite observations, particularly in urban environments. Ambient urban sensing platforms are likely to emerge from technology rollouts associated with smart cities initiatives. Citywide sensing is a foundational technology for many of the trials underway in cities such as Santander (SmartSantander, 2013), Barcelona (BarcelonaSmartCity, 2013), and Amsterdam (Amsterdamsmartcity, 2013). These trials aim to monitor meteorological conditions to identify impacts on citizen safety. These sensor systems will also be used by city managers and planners to monitor remedial interventions, such as planting trees and creating green spaces.

Quantifying the influence of meteorological variables in outdoor environments on human comfort and well-being is challenging due to differences in the physical and biological characteristics of human clothing, context, microclimate influences, and so on. (Honjo, 2009). A number of indices have been developed in an effort to quantify these effects. The most broadly used of these indices are the Standard Effective Temperature (SET*), Predicted Mean Vote (PMV), and Physiological Equivalent Temperature (PET). SET represents the thermal strain experienced by a “standard” person in a “standard” environment. PMV represents the “predicted mean vote” of a large population of people exposed to a certain environment. PMV is derived from the physics of heat transfer combined with an empirical fit to sensation, as shown in Table 11-3. PMV establishes a thermal strain based on steady-state heat transfer between the body and the environment and assigns a comfort vote to that amount of strain. PET was developed as an index that takes into account all basic thermoregulatory processes and is based on a thermo-physiological heat balance model, called the Munich Energy-Balance Model for Individuals (MEMI).

Table 11-3. *Ranges of PMV and PET for different grades of thermal perception and physiological stress*

PMV	PET (°C)	Thermal Perception	Grade of Physiological Stress
-3.5	4	Very cold	Extreme cold stress
-2.5	8	Cold	Strong cold stress
-1.5	13	Cool	Moderate cold stress
-0.5	18		
0.5	23	Slight Cool	Slight cold stress
1.5	29	Comfortable	No thermal stress
2.5	35	Slight Warm	Slight heat stress
3.5	41	Warm	Moderate heat stress
		Hot	Strong heat stress
		Very Hot	Extreme heat stress

From a sensing perspective, the measurements of interest are air temperature, radiant temperature, air speed, and relative humidity. Sensor deployments in cities such as Hong Kong (Cheng et al., 2012), Colombo, Sri Lanka (Johansson et al., 2006), and Glasgow (Krüger et al., 2013) have been reported in the literature. These studies show that sensor-based approaches are useful for identifying and quantifying local influences such as wind speed and solar radiation on thermal comfort, and their influence on human biometeorology—the study of the interactions and relationships between human beings and atmospheric conditions (Höppe, 1997). Additional studies using sensors have looked at how green spaces can have a positive influence on ambient environment, comfort, and improved air quality. Reported studies include Hangzhou (Shuo et al., 2010), New York City (Gaffin et al., 2009), and Tel Aviv (Cohen et al., 2010). While a wide variety of weather apps for smartphones already exist, user-centric weather-monitoring capabilities for smartphones have also started to emerge. Sensordrone, funded under a Kickstarter campaign, has developed a multi-sensor platform small enough to attach to a key ring that can stream data via Bluetooth to a smartphone. It supports a variety of applications, including a mobile weather station. Sensors can monitor humidity, temperature, light intensity, O_3 and CO. A number of apps are available for download, including a relative humidity monitor and an air quality index (which displays measurement of CO, CO_2, temperature, humidity and air pressure) (Sensorcon, 2013).

UVA/UVB Monitoring

The link between exposure to UV radiation and skin cancer is well established. Excessive exposure to UV radiation is a global problem due to ozone depletion in the atmosphere, pollution (Gillette, 2011) and unsafe human behaviors. Lack of exposure to sunlight can also have health implications due to Vitamin D deficiencies. Vitamin D levels are determined by the sum of exposure to UV radiation and dietary intake. Sun exposure in moderation is the major source of Vitamin D for most humans (Holick et al., 2011). In northern latitudes, Vitamin D deficiency is now recognized as being medically significant; it causes rickets in children and is a contributing factor in osteoporosis and osteopenia in older adults. It has also been associated with increased risk of common cancers, autoimmune diseases, and hypertension.

UV radiation is typically subdivided into three components based on wavelength:

- UV-A (wavelengths between 315nm and 400nm)
- UV-B (wavelengths between 280nm and 315 nm)
- UV-C (wavelengths between 200 and 280nm)

UV-C is absorbed by the ozone and normally does not reach the earth's surface. But in the southern hemisphere, where ozone holes can appear, it is an issue. Erythema curves that plot UV wavelength (nm) versus irradiance (W/m^2) are used to determine the UV exposure levels that may damage human skin as a result of sunburn, as shown in Figure 11-9.

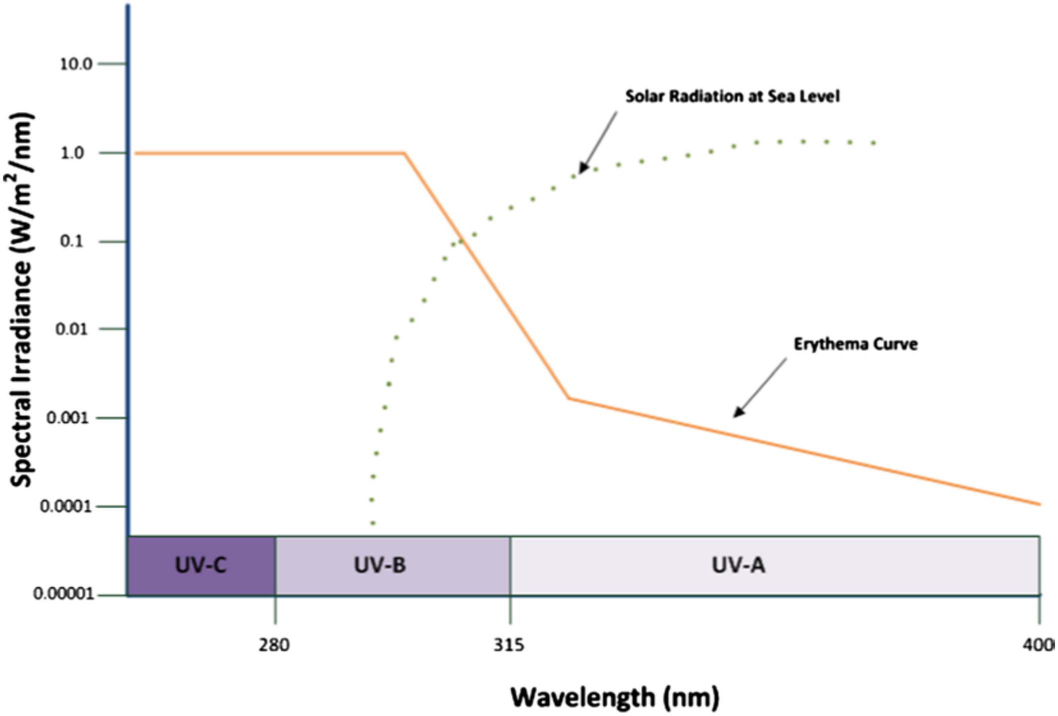


Figure 11-9. *Erythema curve for human skin damage*

UV can be measured in a variety of ways, including instrument radiometers, personal dosimeters, and satellites instruments, such as GOME-2. Sensors in dosimeters generally focus on measuring UV-A/B. In their simplest form, they can be adhesive patches (chemical dosimeters) that stick onto exposed skin (SunSignal, 2013) or wristbands (UVSunSense, 2013). Products are often aimed at parents who want a simple method to monitor their child's exposure. Biological dosimeters measure UV exposure by the rate of mutation induction in microorganisms, for example, Bacillus subtilis (Biosense, 2013). Although they can provide a good estimation of exposure, they can be difficult to manage and analysis can be time-consuming. The most common form of UV-A/B sensing is the electronic dosimeter in various forms, including bodyworn wristwatches such as the Sunsaver, which developed as part of the FP7 ICEPURE project (ICEPURE, 2009).

There are already a variety of UV smartphone apps available, such the EPA UV Index, My UV Check, Sun Safe, and so on. Data used by the apps is generally provided by the local National Weather Service. Converting a smartphone into a personal UV dosimeter has also been demonstrated via the DoCoMo sensor jacket in Japan (Lamkin, 2011). Other initiatives include Sundroid, which is based on a photodiode UV-A/B sensor worn externally on the body and connected to an Android smartphone via Bluetooth. The app running on the phone displays the accumulated UV dose, the current UV index, and the timeline of UV exposure, as shown in Figure 11-10. A detailed view is also available with more comprehensive exposure information. The platform has been applied to a number of use cases, including snowboarding and climbing. (Fahrni et al., 2011). A similar approach has also been reported by MIT's Mobile Experience Lab (Laboratory, 2011).

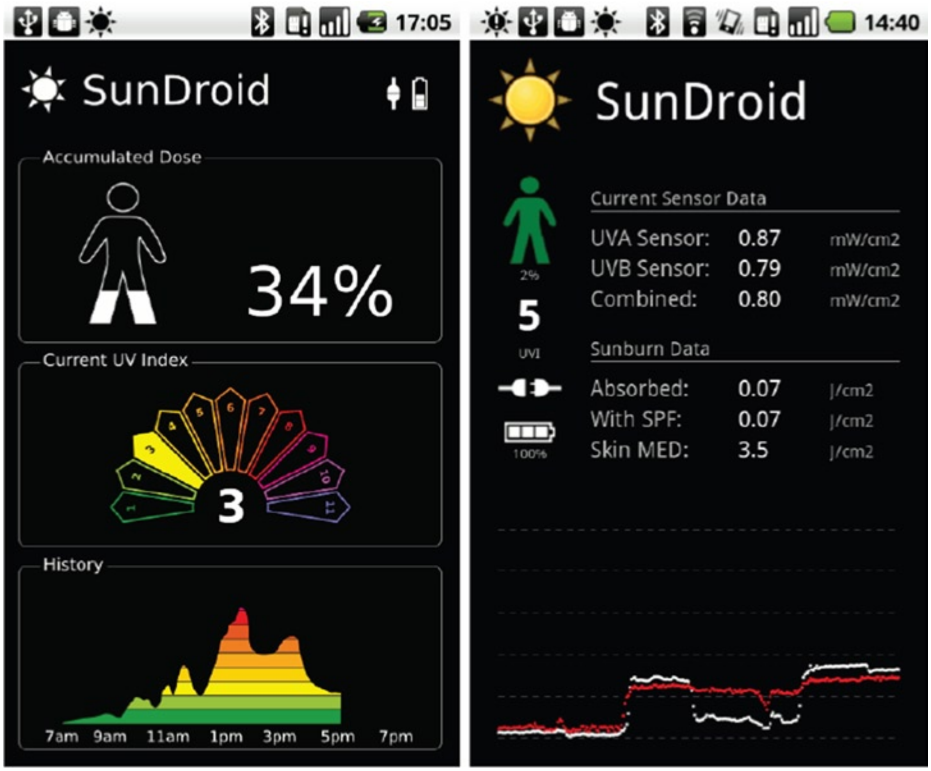


Figure 11-10. *Sundroid activity screens: The Simple View (left) and Advanced View (right) (image used with permission from the Distributed Computing Group, ETH Zurich*

Monitoring UV radiation using a smartphone without a dedicated sensor has been demonstrated by researchers in the University of Southern Queensland. The built-in camera in a smartphone was used to measure UVA irradiance down to 340nm in a feasibility study (Igoe et al., 2013). It is an interesting development, but smartphone camera technology needs to evolve to a point where irradiance can be measured down to 280nm before this approach would be of practical use.

Water Quality Monitoring

The need to accurately monitor water quality continues to grow due to the ever-increasing demand for fresh, clean water all over the world. Urbanization, intensive agriculture methods, food processing, and so forth have increased the demand for water. Meanwhile, these and other human activities have resulted in increased incidences of contaminated water supplies. Concerns about water will only increase as new human activities emerge that impact our environment. New sources of pollutants are emerging that have the potential for significant adverse impact on water quality. For example, shale gas extraction using fracking is causing international controversy. The process uses horizontal drilling with hydraulic fracturing by means of high pressure water and chemicals. There is much heated public debate due to concerns about contamination of water supplies with chemicals used in the fracking process and the release of naturally occurring gases such as methane into underground aquifers. As a result, there is a growing need for water-quality sensing to provide real-time information to complement traditional laboratory analysis. Furthermore, the data from these sensor measurements should be made public to ensure transparency and to keep citizens informed appropriately.

To monitor water quality, a variety of sensor technologies have been utilized. Handheld sensors can be used by scientists to make measurements in situ. Fixed sensing can be integrated into the control systems for public water utilities. Wireless sensor modules can be used to monitor a specific water source, such as the WaterBot project (Carnegie-Mellon, 2013). Some of the key technologies utilized in water-sensing applications to date include electrochemical (Kimmel et al., 2011), biotechnology (Lagarde et al., 2011), MEMS (Jang et al., 2011), nanotechnology (Rassaei et al., 2011), optical (Namour et al., 2010).

Over the past few years, optical sensor and measurement technologies have emerged as a more reliable alternative to electrochemical approaches due to simpler operation. Methods such as optical fluorescence and absorbance are being widely adopted in various applications. The growth of laser and LED technologies are also stimulating the growth of the water-quality monitoring market. For complex analyses that require sample preparation and multi-analyte analysis, lab-on-chip technologies are being developed (Jang et al., 2011). This technology enables miniaturized design and fabrication of laboratory-based techniques on a single chip to deliver the same reliability and efficiency while providing flexibility and portability capabilities.

These types of sensing approaches can be used to measure a wide variety of parameters relevant to the quality of water for human use. The parameters can be classified in three major categories—physical, chemical, and biological. Significant factors that affect water quality include suspended sediments (turbidity); algae (that is, chlorophylls and carotenoids); chemicals (fertilizers, pesticides, and metals); dissolved organic matter (such as sewage); thermal releases (from food processing); aquatic vascular plants; pathogens; and oils. While traditional laboratory methods can provide accurate analysis of these contaminants, they are time-consuming and can only provide delayed results. Laboratory-based quality assurance programs use scheduled sample collection and, therefore, depending on the sampling intervals, anomalous events may go unnoticed. Such undetected changes can be of potential risk to public health. Therefore, there is a growing trend toward real-time analysis capabilities to augment laboratory analysis in an effort to guard public safety.

Companies such as YSI Inc. (`www.ysi.com`), Intellitect Water (`www.intellitect-water.co.uk`), Liqum Oy (`www.liqum.com`), and Optiqua (`www.optiqua.com`) provide real-time quality-sensing systems that can detect key physical and chemical characteristics of water. Real-time sensing capabilities will play a vital role in the evolution of smart water systems. In these systems sensing and management technologies will be used to optimize the availability, delivery, utilization, and quality of water, together with others systems such as water treatment management. Companies like IBM are working with public authorities such as Sonoma County Water Agency in California and the Beacon Institute on the Hudson River in New York to deliver the first generation of these systems (IBM, 2010, Beacon Institute, 2007).

In an approach that is analogous to some of the crowdsourcing efforts in air quality, the Don't Flush Me project in New York City is focused on reducing sewage overspill into the Hudson River by modifying citizen behavior. The initial prototype involves an Arduinio-based proximity sensor and mobile phone that measure the water level in sewers. If the water levels are high enough to result in overflow into the river, various forms of visual feedback are created to encourage citizens to reduce their waste output. This feedback includes a web site with area-specific indicators, SMS messaging, and an Internet-connected light bulb. Later versions of the platform have used temperature and conductivity to detect sewage overflow into the river. (Percifield, 2012).

The Argo project has deployed a global array of more than 3,600 autonomous sensor floats to measure temperature and salinity in the oceans. Each float sinks to a prescribed drifting depth of 1000 to 2000m, (1300–6500 ft.) where it remains for about 10 days. It then rises to the surface, collecting temperature and salinity data. The float remains at the surface while it transmits its position and sensor data to a satellite, then sinks back down to its prescribed drifting depth, completing the collection cycle and starting a new one. Other types of sensors—for pH, oxygen, and nitrate levels—are currently in development or being evaluated. Data from the project is freely available for anyone to use in various research domains, including climate, weather, oceanographic, and fisheries (Kramer, 2013).

Physical Water Sensing

A number of sensors are available for the continuous monitoring of the physical characteristics of water; the most commonly measured characteristics are shown in Table 11-4.

Table 11-4. *Sensor-Based Physical Water Quality Analysis*

Characteristic	Description	Sensor
Temperature	Water temperature influences its density, the solubility of constituents, pH, specific conductance, the rate of chemical reactions, and biological activity.	Thermistor
Conductivity	Measurement of the capacity of water to conduct an electrical current. Conductivity is a function of the concentrations and types of dissolved solids, such as metals, inorganics, and organics. Changes in conductivity can result from discharges into the water. Sewage, for example, raises conductivity due the presence of chloride, phosphate, and nitrate. In contrast, an oil spill may cause a drop in conductivity due to the presence of organic compounds.	Conductivity Electrode
Color	Apparent color is the color of the water sample as a whole, which is affected by both dissolved and suspended compounds. True color is obtained after filtering the water to remove all suspended material. The health impact of color depends on the type of dissolved compounds.	Optical *Colorimeter*
Turbidity	Turbidity is the cloudiness of a water sample, caused by suspended particles or impurities may include clay, silt, vegetable matter, soluble colored organic compounds, algae, and microorganisms. Excessive turbidity in drinking water is aesthetically unappealing and may also represent a health concern, resulting in issues such as gastroenteritis.	Optical *Nephelometer* *Surface Scatter Method*

Chemical Water Sensing

Sensors used for chemical analysis of water quality measure a variety of organic and inorganic elements and molecules that are either dissolved or suspended in water. Sensors based on electrochemical or optical techniques can be used to detect pollutants such as nitrates or heavy metals in real-time. Common chemical parameters of interest that can be measured by sensors, include pH, hardness, nitrates, phosphates, and dissolved oxygen, are presented in Table 11-5.

Table 11-5. *Common Sensor Approaches Used for Chemical Water Quality Analysis*

Characteristic	Description	Sensor
Dissolved Oxygen	Adequate dissolved oxygen (O_2) is necessary for good water quality. The main factor contributing to changes in dissolved oxygen levels is the build-up of organic wastes. Low levels of dissolved oxygen maybe indicative of microorganisms in the water consuming oxygen as they decompose sewage, urban and agricultural runoff, and discharge from food-processing plants	Electrochemical *Amperometric* *Galvanic* *Polarography* Gas Optical *Luminescence* Biosensor
pH	The pH of a water sample relates to the concentration of hydrogen ions. Drinking water has a pH range of 6.5 to 9.5. Extreme pH values can indicate chemical spills, treatment plant issues, or problems with the supply pipe network.	Electrometric *Potentiometric* ISFET Optical *Colorimetric*

(*continued*)

Table 11-5. (*continued*)

Characteristic	Description	Sensor
Chlorine	As ground water percolates underground through bedrock or sand and gravel, it dissolves various minerals and constituents, including chloride. Chloride (Cl^-)levels in wells and reservoirs that are higher than normal may indicate pollution such as sewage, industrial contamination, fertilizers, and so on.	Electrochemical *Amperometric* Optical *Colorimetric*
ORP	The oxidation-reduction potential (ORP) of a water sample is a key measure of how well a water treatment or sanitization process is working. It is used to monitor drinking water, swimming pools, and spas. ORP targets are expressed in millivolts, which can be determined for each specific application and will result in completely reliable disinfection of pathogens.	Electrochemical *Potentiometric*
Free Chlorine	Free chlorine is formed by the reaction of chlorine gas with water. This molecule and its ion are essential in ensuring that water is safe to drink. They act as oxidizing agents (disinfectants), killing bacteria. Excess chlorine in drinking water has been linked with bladder and rectal cancers.	Electrochemical *Polarography* *Amperometric* Optical *Colorimetric*
Heavy Metals	Common heavy metals, such as cadmium (Cd), copper (CU), mercury (Hg), and lead (Pb), in water have been linked to a variety of health risks, including reduced growth and development, cancer, organ damage, nervous system damage, and, in extreme cases, death. Young children are particularly susceptible to the toxic effects of heavy metals.	Electrochemical *ISE* *ISFET* Optical *Photoluminescence* *Fluorescence*
Phosphate	Phosphates ($PO^{3-}{}_4$) are naturally absorbed in water from bedrock and other mineral deposits. Human and animal waste, washing powder and detergents, and fertilizers in the water supply can cause an increased level of phosphates. This can lead to water-quality problems, including algal blooms, and impacts to human health, such as kidney damage and osteoporosis.	Optical *Colorimetric* Electrochemical *Potentiometric ISE*
Nitrate	Nitrate (NO_3^-) is an inorganic compound that is highly soluble in water. Major sources of nitrates in drinking water include fertilizers, sewage and animal manure. When ingested, nitrate is converted to nitrite in the body. Nitrite can result in health issues, particularly for young children. In infants it can cause methemoglobinemia or blue-baby syndrome. It has also been linked to cancers through the formation of nitrosamines, which are known cancer-causing agents.	Electrochemical *Potentiometric ISE* Optical *UV Absorption* *Fluorescence*

Biological Pathogen Water Sensing

Biological water sensing focuses on the detection of pathogens or related products that can impact human health. The presence of biological contaminants is normally regulated. For example, in the U.S., the Safe Drinking Water Act (SDWA) and the Clean Water Act (CWA) address microbial contamination in water. The CWA is designed to protect surface water for drinking, aquatic food sources, and recreational use. The SDWA provides a regulatory framework to manage drinking water for human consumption and to protect source waters (EPA, 2012).

Many types of pathogens can be found in contaminated water, such Escherichia coli (E. coli), Cryptosporidium, and Giardia lambilia. Most of the current techniques require overnight culture to produce high cell numbers before visual screening to confirm the presence of a pathogen, which is time-consuming. As a result, significant numbers of individuals may be infected before an issue is detected, the public is informed, and boil notices are put in place. Sensors provide an attractive way to quickly detect microbial contamination. But the development of such technologies is challenging, with few sensors commercially available at present. This continues to be an area of active research, though, with promising developments in DNA-based biosensing for species-specific determination of bacteria starting to emerge. Table 11-6 outlines the sensors currently available for biological water-quality monitoring.

Table 11-6. *Common Sensor Approaches for the Identification of Biological Contamination in Water*

Characteristic	Description	Sensor
Blue-Green Algae (cyanobacteria)	Cyanobacteria (blue-green algae) is a bacteria that has the potential to cause health problems in humans and animals. Cyanobacteria are common and naturally occurring, but water pollution, such as sewage effluent, fertilizer run-off, sediment, and food-processing effluent, can cause some types to form dense blooms. Toxins released by the bacteria can cause nausea, vomiting, abdominal pain and diarrhea.	Optical *fluorescence*
Chlorophyll	Chlorophyll is produced by phytoplankton. It does not negatively impact human health and has been reported to actually have beneficial effects. However, the presence of chlorophyll may indicate high nutrient levels, perhaps from fertilizer runoff, which could impact human health.	Optical *fluorescence*
Cryptosporidium	Cryptosporidium is a protozoan parasite that causes a severe diarrhea disease known as cryptosporidiosis. Both human and animal waste are potential sources of contamination. Outbreaks of the disease are normally associated with poor water treatment. Cryptosporidium oocysts are resistant to chlorine disinfection, so the water treatment process must be tightly controlled. Oocyst removal is achieved with effective clarification and filtration stages during the treatment process.	*Biosensor* (*research*)
Coliforms E. Coli	Human consumption of water contaminated with E. coli results in nausea, vomiting, abdominal pain, diarrhea, and even death in severe cases. E. coli can result from sewage contamination in water.	Biosensor (research)

Mobile Water-Quality Sensing

As with many other areas of sensing described in this book, water-quality monitoring applications are beginning to emerge for mobile form factors. Smartphones have started to replace the dedicated data loggers that have been used with handheld sensors for in-situ sensing for many years. For example, In-Situ Inc. (`www.in-situ.com`) recently announced its iSitu smartphone app, which can connect via Bluetooth to its handheld probe that includes an optical dissolved-oxygen sensor, as well as sensors for barometric pressure, air temperature, and water temperature. The phone's GPS can be used to geotag the sensor readings together with photos from the smartphone camera. Data can also be sent in real-time to any required location, giving the field operators flexibility in delivering information to their offices and receiving instructional updates In a related application, Insta-link provides a smartphone app that can be used to scan a test-strip for free chlorine, pH, alkalinity, hardness, and cyanuric acid to determine if water quality in a pool or spa is sufficient for human recreational purposes (Insta-Link, 2012).

The development of smartphone water-quality sensors has also become the focus of community initiatives. The MoboSens campaign, for example, is developing a smartphone-based sensor to provide accurate nitrate measurements. MoboSens hopes the platform will provide citizens with the capability to collect and share water-quality data via social media, with a view to improving public safety by augmenting existing institutional sensing. There are plans to extend the sensing functionality of the platform to include the detection of arsenic, heavy metal ions, bacteria and radioactivity (Edgar, 2013). Another community initiative is the Sensordrone multi-sensor tool. Sensors for pH and dissolved-oxygen measurements are under development to complement their existing ambient environmental sensing platform (Sensorcon, 2013).

The combination of sensing and mobile devices for water-quality measurements, though in the early stages, promises a powerful capability. Discrete water quality readings, together with geographical tagging and temporal information collected and shared by citizens, can be used to generate community water-quality maps. Concerned citizens will be able to test their water supply on a regular basis and upload the data. This will help promote communal knowledge of local water quality and how it varies over time. It will allow citizens to rapidly identify influences impacting water quality. This approach has the potential to become the environmental equivalent of the quantified-self movement (see Chapter 7) in the health domain—that is, the collective identification of early signs that there may be something wrong with the local water quality.

Environmental Noise Pollution

Noise pollution keeps growing, particularly with increased urbanization, industrialization, and air traffic. The EPA describes noise pollution as *"sound that becomes unwanted when it either interferes with normal activities such as sleeping, conversation, or disrupts or diminishes one's quality of life."* The correlation between health and noise has been well-established in a number of studies. Problems connected to noise pollution include stress-related illnesses, high blood pressure, speech interference, hearing loss, sleep disruption, and lost productivity. Individuals and community groups are embracing sensing technologies, and leveraging their smartphones with apps such as Sound Meter. Home environmental sensing platforms such as CubeSensors also have integrated noise-level monitoring capabilities. Such approaches help to improve the spatial and temporal granularity of data, which can be limited in official noise surveys. Data from these surveys is often used to extrapolate dispersed measurements to wider geographical areas without sufficient consideration of influences such as open spaces, building types, green areas, traffic flows, and so forth.

Crowdsourcing as a means to generate noise pollution maps in urban areas has been a focus of the research community, leading to the development of a number of platforms. The NoiseTube project uses a crowdsourcing approach based on smartphones. The app running on the phone collects noise level, GPS coordinates, time, and user input. The application contains a real-time signal-processing algorithm that measures the loudness of the environmental sound recorded via the microphone. A real-time visualization is displayed on the phone, with color-coded values to indicate the health risk of the current exposure level. The application also allows the user to annotate the data to provide context information about the source of the noise. The collected data is used to build noise maps using Google Earth. It is envisaged that these maps and user-generated environment logs or "elogs" can help citizens to make local officials aware of noise pollution issues and their social implications (Maisonneuve et al., 2009). Similar smartphone sensing platforms have been deployed in city environments such as Ear-Phone in Brisbane, Australia (Rana et al., 2010) and NoiseSPY in Cambridge, UK (Kanjo, 2010).

In an effort to quantify the body's response to noise pollution, the SMART-Band was developed to sense skin conductance and temperature. This approach is built on the concept of using humans as sensors in their environment. The sensor is intended to translate subjective feelings and emotions into quantifiable measurements. An 18-person trial was conducted in the city center of Kaiserslautern to examine the effect of noise on emotional well-being. A number of areas in the city with different noise levels were selected, varying from areas of high noise pollution from city traffic to quieter inner-city parks. Standalone sensors were used to measure noise levels. The study generated limited results and findings due to issues with the body-worn sensors (Bergner et al., 2012). The issues reported are not unexpected, due to the difficulties in collecting reliable and reproducible skin conductance sensor data. Problems such as baseline drift, reliable contacts, and the development of robust correlations to various emotional states are challenging. However, the concept gives us insights into how in the future we may use sensing to determine the effects of the environment on our health and wellness, and to influence changes in behavior. Building on the concept of humans as sensors and adding gamification (using principles of game play to boost participation and engagement) into the mix, researchers at University Jaume I in Spain are developing a noise-tracking game, NoiseBattle, for Android smartphones. Game players are required to move around a city, taking noise samples with the goal of completing a noise map for the city (Martí et al., 2012).

Radiation Sensing

Radiation exposure is a topic that strikes fear in the public mind. Accidents, such as those at Chernobyl and Fukushima, have only increased these fears. For most people, exposure to radiation from such incidents is of little real concern. However, a natural radiation threat can exist in some people's homes in the form of dangerous levels of radon gas. Radon gas comes from uranium decay in soil and can enter homes through cracks in foundations, ventilation openings, and so on. Radon is the second leading cause of lung cancer, after cigarette smoking, with an estimated 21,000 lung cancer deaths alone in the U.S. each year (EPA, 2013). Testing for radon normally involves in-home air sampling over a defined period, with the sampling unit then sent to a laboratory for analysis. Sensors are now available that can provide continuous monitoring of the gas, the levels of which can vary significantly. Sensors such as the Safety Siren Pro 3 Radon Gas Detector from Family Safety Products provide continuous monitoring with an audio alarm if the levels of radon exceed safe limits.

The 2011 nuclear power plant disaster at Fukushima in Japan resulted in a huge environmental impact that required the evacuation over 150,000 people from a 20 mile-exclusion zone around the plant. For people near the exclusion zone, access to data on radiation levels was a significant concern. Due to a lack of trust and resolution in the available radiation level data, a community-led initiative using online data platforms such as Xively and citizen-contributed radiation measurements facilitated better access to data among the general public. However, the limited availability of local radiation-measurement capabilities led the Spanish company Libelium to initiate an international community-based project to develop a wireless radiation sensor. A radiation sensor board for Arduinio was quickly built and validated (see Figure 11-11). The design of the board was based on open hardware and the source code was released under a general public license. The sensor platform provided a means for local engineers to collect data in communities around Fukushima and to make that data publically available to concerned citizens (Boyd, 2011). In a similar manner, the problems at Fukushima acted as the catalyst for the formation of Safecast, a global sensor network based on community efforts to collect and share radiation measurements with a view to empowering people with information about the safety of their environment. All data collected by Safecast using mobile, handheld, and fixed sensing is made publicly available under creative commons rights (Safecast, 2013).

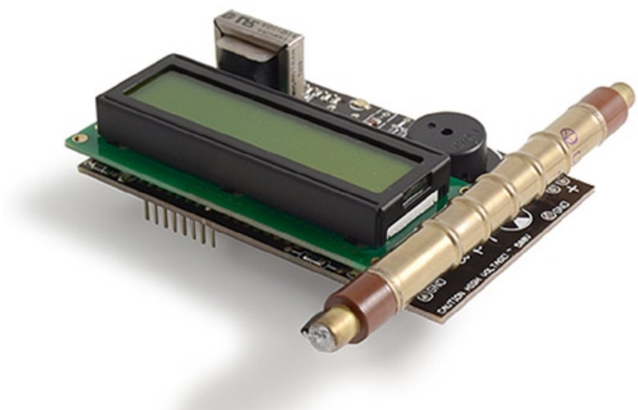


Figure 11-11. *Libelium's Radiation Sensor Board for Arduino (image used with permission from Libelium)*

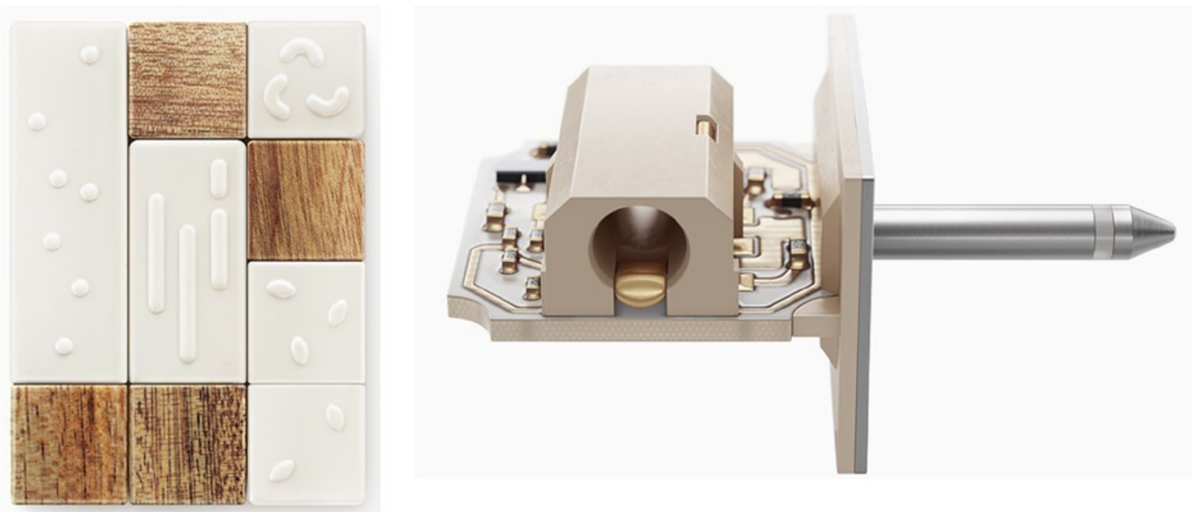
Environmental Impact on Food

The use of sensor technologies to monitor agricultural production has been an area of research for many years. In recent years, commercial wireless sensor network products have emerged that target commercial agriculture. The use of technology in agricultural production is likely to increase as we become more concerned about food security. For example, Libelium is already targeting this market with its Waspmote Agriculture Board. This board supports the monitoring of multiple environmental parameters, including air and soil temperature and humidity, solar visible radiation, wind speed and direction, rainfall, atmospheric pressure, and leaf wetness.

Such sensing technologies are designed to reduce human-resource requirements during the growing cycle. Optimal growth parameters, such as soil moisture content, can be defined for a crop. When the sensor readings detect that conditions are not optimal, the data can be used to automatically switch on the irrigation system. This helps maintain optimal growing conditions while restricting water use to only what is necessary. The use of sensors in agriculture, food production, and food logistics is an extensive topic and beyond the scope of this chapter. However, sensor technologies that measure environmental impact on quality are starting to emerge for consumers.

The use of intensive agricultural methods, including the pervasive use of fertilizers and pesticides, has been the subject of much public debate over the last decade with regard to their effects on food quality and safety. As a result, many people are turning to organically produced foods. In China, there is significant concern about food safety based on a number of recent scandals. For example, the Sanlu Group was found to have sold milk powder contaminated with melamine, an industrial compound used to create plastic that makes milk appear protein-rich (Lawrence, 2008). As a result, sensor technologies for consumer use targeting food safety concerns are starting to emerge.

One particular sensor platform that is focused on environmental and food sensing is the Lapka personal environmental monitor. This is multisensory platform has an aesthetically appealing form factor, as shown in Figure 11-12 (a). The platform has sensor modules for radiation, electromagnetic field (EMF), humidity, and organic measurements. Data from the sensors is streamed to an iPhone app via a wired connection. The organic sensor module is used to detect significant quantities of nitrates in raw produce, which may originate from the use of synthetic fertilizers, according to Lapka. The stainless steel probe, shown in Figure 11-11 (b), is inserted into any fruit or vegetable included on a preset list, which contains a defined limit for nitrate concentrations. Conductivity that significantly exceeds the limits apparently suggests the use of nonorganic farming practices. The sensor has an operational range of 0-5000 ppm NO_3^-.



(a)

(b)

Figure 11-12. *(a) Lapka's integrated sensors (b) The organic sensor module (images used with permission from Lapka)*

Such sensing capabilities are likely to appeal to health-conscious consumers. A variety of new sensors that measure various environmental impacts on our food quality and safety are likely to emerge in the near future. But significant challenges are also likely to materialize, in particular, distinguishing between inorganic compounds that occur naturally due to the underlying geology of where food is grown, and those that are introduced artificially through intensive agricultural production methods. Geotagging of food sources is one potential initiative where natural background levels in water and soils can be measured by citizens to create maps of farm regions. These maps can then be used as a reference against parameters measured in food samples. Consumer-oriented sensing in the food domain is still in its infancy. There will certainly be public debate as to the respective merits of various sensor products as they emerge in the marketplace. Ultimately, consumers will determine whether they are successful and offer meaningful data.

Future Directions for Environmental Monitoring

The market for environmental sensing and monitoring is estimated to be growing by 6.5 percent per year and is expected to be valued at $15.6B USD by 2016. A significant portion of this value will be related to institutional and regulatory activities, but there will also be a growing consumer element. Sensors and applications that extend the concept of the quantified self into the living environment will continue to evolve. These technologies will enable interesting new use cases, delivering new insights into the environment around us and how it impacts our health and wellness.

The first wave of these products has already reached the consumer market. The fact that the initial batches of some products sold out, for example, CubeSensors (Isakovic, 2013), illustrates an obvious public appetite for this information, whether it be air quality, noise pollution, or determining whether food is organic. As with the other forms of sensing discussed in this book, mobile devices are the key enabling platform, providing convenient and intuitive data access points through accompanying apps for the sensors. These apps act primarily as simple visualization portals for the data. But elements of intelligent data processing and prediction using cloud-based services are starting to emerge. This is an area likely to see interesting developments in the coming years. Some products are already using pattern-recognition techniques to tell users how to modify their environment. Simple actions, such as increasing the ventilation in a room to raise oxygen levels and decrease CO_2, can be identified. These actions have the simple goal of improving the wellness of people in their homes. In the future, such systems will be able to indicate the best time to exercise based on measurements of the weather, air quality, and physiological status. Or they may suggest an alternative route to work or school if the pollen count is above safe levels on the normal route.

The convergence of health, wellness, and environmental sensing will continue to grow and deliver a more holistic approach to maintaining our health and wellness. Already in the research domain we are seeing the emergence of multi-sensor techniques that look at the impact of environmental parameters on our physiological and psychological well-being. Emerging crowdsourced environmental applications, where humans become mobile sensors in their environments, are utilizing these technologies in interesting ways. Such initiatives are likely to have growing importance in how citizens manage and modify their living environments to ensure the health of all citizens.

In the future, citizen sensors will play a growing role as mobile data sources in an ambient intelligent environment. The role of human sensing will also evolve beyond the current solutions of smartphone and discrete sensors deployed in our homes or other environment to modalities that are both organic and natural. For example, concepts for clothing that can act as environmental pollution monitors are already emerging. A collaboration between diffus.dk, Alexandra Institute, The Danish Design School, and embroidery company Forster Rohner has produced a dress that indicates $C0_2$ levels by illuminating integrated LED lights (Johannesen, 2009). In a related approach, a dress that contains pH-sensitive dyes that change color in response of the acidity or alkalinity of rain has also been created (Chua, 2012). New materials, including nanomaterials, will emerge that have switchable behaviors, including color, polarity, and porosity, related to environmental stimuli such as pollutants. It will be possible to integrate these materials into wearable fabrics to add ambient intelligence capabilities, such as warning and protecting the wearer from environmental threats, including pollution. This fusion of environmental sensing and clothing, though still experimental, may soon lead to some interesting practical use cases of wearable technologies. Potentially important use cases aside from pollution monitoring may include the detection of hazardous gases, which could greatly help to protect emergency services personnel.

However, many challenges must be overcome before we can truly benefit from advances in environmental sensing. Key among these is improving the quality of sensors at affordable price points. Many of the current consumer products utilize semiconductor sensors, which may have poor sensitivity and may not be particularly selective for the compound of interest. These sensors may also experience drift, and without frequent calibration the data will often contain significant errors. The development of low cost, stable, and sensitive sensors is critical to the future of this domain.

In the biological-sensing domain, the use of sensors to determine species-specific bacterial contamination or the presence of other biological species is still in its infancy. However, the need for these sensor technologies is ever-present, with an estimated 3.4 million people dying each year from water-, sanitation-, and hygiene-related causes (Lees, 2013). Future developments in biotechnology, optics, and packaging technologies will enable these sensing technologies to move from the laboratory into real world use (Banna et al., 2013). In other domains, such as sensing of chemical components in water, a variety of optical sensing technologies have emerged. Optical sensing approaches can provide improvements in performance stability over traditional electrochemical sensing approaches. They are also starting to approach the sensitivity levels of electrochemical sensors in some cases (Namour et al., 2010, Pellerin et al., 2009). As always, translating promising research into reliable and effective real-world applications is challenging. However, successful new innovations will continue to emerge, building on the lessons learned from current deployments of sensing technologies.

Although the use of discrete sensors is gaining steady momentum for individual use, wireless sensor networks for environmental applications still have significant challenges to overcome, and truly scalable deployments of WSNs have yet to be achieved. A review by Corke et al., points out that networks to date are typically small in size (generally <30 nodes) and are deployed for relatively short periods of time (weeks or months). They argue that technical and cost elements of sensors make widespread environmental monitoring with hundreds or thousands of nodes generally not economically feasible. However, a few areas of significant scientific interest, such as improved understanding of greenhouse-gas emissions and innovative water monitoring, have the potential to see increased investment in large-scale, long-term monitoring initiatives (Corke et al., 2010).

What is certain is that independent of the sensing modality, we will have greater access to data about our environment and that we will play an integral and active role in sensing our environment. As the technology evolves and the quality and breadth of sensor data increases, the potential use of the data will be limited only by our insight. At a minimum, we will have a better understanding of the dynamic nature of the relationship between our health and wellness and the environments in which we work, live and play.

Summary

This chapter has looked how sensors can be used to monitor key aspects of our environment, such as air and water quality, exposure to solar and radioisotope radiation, and noise pollution. Global stressors, such as urbanization, industrialization, and a variety of human activities are increasing the pressure on our environmental integrity, resulting in an ever-growing need to monitor environmental resources. New sensing technologies and applications are emerging that are designed to empower individuals with data and knowledge about their ambient environment. This data can be used by individuals to better understand the relationship between their environment and their health and wellness. Sensors designed for personal use are also catalyzing community-led initiatives. Citizens can participate in the collection and sharing of data on key environmental parameters, such as air quality. Such approaches have the potential to provide scalable sensing capabilities that are not possible with traditional institutional monitoring regimes.

References

Barnoya, Joaquin and Stanton A. Glantz, "Cardiovascular Effects of Secondhand Smoke Nearly as Large as Smoking," *Circulation,* vol. 111 pp. 2684–2698, 2005.

Sasco, A. J., M. B. Secretan, and K. Straif, "Tobacco smoking and cancer: a brief review of recent epidemiological evidence," *Lung Cancer,* vol. 45, Supplement 2 (0), pp. S3–S9, 2004.

Bretveld, Reini, Marijn Brouwers, Inge Ebisch, and Nel Roeleveld, "Influence of pesticides on male fertility," *Scandinavian Journal of Work, Environment & Health,* vol. 33 (1), pp. 13–28, 2007.

Balabanic, Damjan, Marjan Rupnik, and Aleksandra Krivograd Klemencic, "Negative impact of endocrine-disrupting compounds on human reproductive health," *Reproduction, Fertility and Development,* vol. 23 (3), pp. 403–416, 2011.

IHME, "The Global Burden of Disease: Generating Evidence, Guiding Policy", Institute for Health Metrics and Evaluation, Seattle, Washington, 2013.

Quantified Self Labs, "Quantified Self - self knowledge through number ", http://quantifiedself.com/, 2012.

Linear-Technology, "Wireless Sensor Network Challenges and Solutions", http://cds.linear.com/docs/en/white-paper/wp001fa.pdf, 2012.

Ghosh, Amitabha and Sajal K. Das, "Coverage and connectivity issues in wireless sensor networks: A survey," *Pervasive and Mobile Computing,* vol. 4 (3), pp. 303–334, 2008.

Mainwaring, Keith and Lara Srivastava, "The Internet of Things - Setting the Standards," in *The Internet of Things: Connecting Objects*, Chaouchi, Hakima, Ed., Hoboken, New Jersey, Wiley, 2010, pp. 208–2010.

Conway, Maura, "What is Cyberterrorism and How Real is the Threat?," in *Law, Policy, and Technology*, Reich, Pauline C. and Eduardo Gelbstein, Eds., Hershey PA, IGI Global, 2012, pp. 279–307.

Zervous, Barry. "*Q&A on energy harvesting, wireless sensors, wireless sensor networks*," Last Update: April 4th 2013, http://www.energyharvestingjournal.com/articles/q-amp-a-on-energy-harvesting-wireless-sensors-wireless-sensor-networks-00005316.asp

Boisvert, Sarah. "*3D printing enclosures for micro wireless sensors and circuits inexpensive and practical solution for company*," Last Update: 2013, http://www.3dprinter.net/3d-printing-enclosures-for-micro-wireless-sensors-and-circuits

Crisostomo, Christian, "*Monitor Air Pollution with Smartphone Accessed Portable Sensors*", The Environmental Blog.org, Last Update: January 20th 2013, http://www.theenvironmentalblog.org/2013/01/monitor-air-pollution-smartphone-accessed-portable-sensors/

Sensorcon. "*Make Sensordrone Do Even More*," Last Update: 2013, http://www.sensorcon.com/sensordrone-extensions/

Choi, Sukwon, Nakyoung Kim, Hojung Cha, and Rhan Ha, "Micro Sensor Node for Air Pollutant Monitoring: Hardware and Software Issues," *Sensors,* vol. 9 pp. 7970–7987, 2009.

Romain, A. C. and J. Nicolas, "Long term stability of metal oxide-based gas sensors for e-nose environmental applications: An overview," *Sensors and Actuators B: Chemical,* vol. 146 (2), pp. 502–506, 2010.

Grossi, M., *et al.*, "A Portable Sensor With Disposable Electrodes for Water Bacterial Quality Assessment," *Sensors Journal, IEEE,* vol. 13 (5), pp. 1775–1782, 2013.

Mannoor, Manu S., Siyan Zhang, A. James Link, and Michael C. McAlpine, "Electrical detection of pathogenic bacteria via immobilized antimicrobial peptides," *Proceedings of the National Academy of Sciences,* vol. 107 (45), pp. 19207–19212, 2010.

Department of Environment and Heritage Protection - Queensland Government, "Sulfur Dioxide", http://www.ehp.qld.gov.au/air/pollution/pollutants/sulfur-dioxide.html, 2011.

EPA. "*Mobile Air Monitoring on the Gulf Coast: TAGA Buses*," Last Update: 2010, http://www.epa.gov/bpspill/taga.html

Standards, European, "http://www.en-standard.eu/csn-en-12341-air-quality-determination-of-the-pm10-fraction-of-suspended-particulate-matter-reference-method-and-field-test-procedure-to-demonstrate-reference-equivalence-of-measurement-methods/Air " vol. CSN EN 12341, ed: European Standards, 1998.

EPA, "National Ambient Air Quality Standards for Lead; Final Rule," vol. 73 FR 66964 ed. United US Environmental Protection Agency 2008.

Evironemental Protection Agency-Ireland, "What is the Air Quality Index for Health", http://www.epa.ie/air/quality/index/#d.en.51765, 2013.

EPA. "*Air Quality Index (AQI) - A Guide to Air Quality and Your Health*," Last Update: May 17th 2013, http://www.airnow.gov/index.cfm?action=aqibasics.aqi#good

The World Data Centre for Remote Sensing of the Atmosphere (WDC-RSAT), "GOME-2 Global Ozone Monitoring Experiment", http://wdc.dlr.de/sensors/gome2/, 2103.

CBS. "*NASA releases images of Beijing air pollution*," Last Update: January 15th 2013, http://www.cbsnews.com/8301-205_162-57564051/nasa-releases-images-of-beijing-air-pollution/

Hidy, George, *et al.*, "Remote Sensing of Particulate Pollution from Space: Have We Reached the Promised Land?," *Journal of the Air & Waste Management Association,* vol. 59 (6), pp. 645–675, 2009.

MedLibrary.org. "*Satellite temperature measurements*," Last Update: 2013, http://medlibrary.org/medwiki/Satellite_temperature_measurements

Jen-Hao, Liu, *et al.*, "Developed urban air quality monitoring system based on wireless sensor networks," in *Sensing Technology (ICST), 2011 Fifth International Conference on*, 2011, pp. 549–554.

Murty, R., *et al.*, "Citysense: An urban-scale wireless sensor network and testbed," presented at the IEEE International Conference on Technologies for Homeland Security, Boston, MA, 2008.

Morreale, P., *et al.*, "Real-Time Environmental Monitoring and Notification for Public Safety," *MultiMedia, IEEE,* vol. 17 (2), pp. 4–11, 2010.

Bagula, Antoine, Marco Zennaro, Gordon Inggs, Simon Scott, and David Gascon, "Ubiquitous Sensor Networking for Development (USN4D): An Application to Pollution Monitoring," *Sensors,* vol. 12 (1), pp. 391–414, 2012.

Li, Jason Jingshi, Boi Faltings, Olga Saukh, David Hasenfratz, and Jan Beutel, "Sensing the Air We Breathe — The OpenSense Zurich Dataset," in *Proceedings of the Twenty-Sixth AAAI on Artificial Intelligence*, Toronto, Ontario, Canada, 2012, pp. 323–325.

Swiss Federal Laboratories for Materials Science and Technology "Empa - a Research Institute of the ETH Domain", http://www.empa.ch/plugin/template/empa/4/*/---/l=2, 2013.

Hasenfratz, David, Olga Saukh, and Lothar Thiele, "On-the-Fly Calibration of Low-Cost Gas Sensors," in *Wireless Sensor Networks*. vol. 7158, Picco, GianPietro and Wendi Heinzelman, Eds., Springer Berlin Heidelberg, 2012, pp. 228–244.

Keller, M., J. Beutel, O. Saukh, and L. Thiele, "Visualizing large sensor network data sets in space and time with vizzly," in *Local Computer Networks Workshops (LCN Workshops), 2012 IEEE 37th Conference on*, 2012, pp. 925–933.

Nafis, Chris. "*Air Quality Monitoring*," Last Update: 2012, http://www.howmuchsnow.com/arduino/airquality/

Jiang, Yifei, *et al.*, "MAQS: a personalized mobile sensing system for indoor air quality monitoring," presented at the Proceedings of the 13th international conference on Ubiquitous computing, Beijing, China, 2011.

Wright, Anne, Candide Kemmler, and Rich Gibson. "*BodyTrack: Open Source Tools for Health Empowerment through Self-Tracking*," Last Update: July 18th 2012, http://www.oscon.com/oscon2012/public/schedule/detail/24733

Aoki, Paul M., *et al.*, "Common Sense: Mobile Environmental Sensing Platforms to Support Community Action and Citizen Science", Computer Interaction Institute http://www.paulos.net/papers/2008/CommonSense%20UbiComp2008Demo.pdf, 2008.

Westly, Erica. "*Citizen Science: How Smartphones Can Aid Scientific Research*," Last Update: 2009, http://www.popularmechanics.com/science/4308375

Zappi, Piero, Elizabeth Bales, Jing Hong Park, William Griswold, and Tajana Šimunić Rosing, "The CitiSense Air Quality Monitoring Mobile Sensor Node," presented at the 2nd International Workshop on Mobile Sensing (ISPN'12), Beijing, China, 2012.

The Copenhagen Wheel, "The Copenhagen Wheel", http://senseable.mit.edu/copenhagenwheel/index.html, 2013.

Mendez, D., A. J. Perez, M. A. Labrador, and J. J. Marron, "P-Sense: A participatory sensing system for air pollution monitoring and control," in *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2011 IEEE International Conference on*, 2011, pp. 344–347.

Saavedra, Joe. "*Citizen Sensor - DIY Environmental Monitoring - Development Blog*," Last Update: 2013, http://thesis.jmsaavedra.com/concept/

Ganapati, Priya. "*Android App Uses Cellphone Camera to Measure Air Pollution*," Last Update: September 24th 2010, http://www.wired.com/gadgetlab/2010/09/cellphone-camera-air-pollution/

Sensaris. "*Discover of SensPods*," Last Update: 2013, http://www.sensaris.com/products/senspod/

SmartSantander. "*Smart Santander*," Last Update: 2013, http://www.smartsantander.eu/

BarcelonaSmartCity. "*Barcelona Ciutat Intel·ligent*," Last Update: 2013, http://smartbarcelona.cat/en/

Amsterdamsmartcity. "*Amsterdam Smart City*", Last Update: 2013, http://amsterdamsmartcity.com/

Honjo, Tsuyoshi, "Thermal Comfort in Outdoor Environment," *Global Environmental Research,* vol. 13 pp. 43–47, 2009.

Cheng, Vicky, Edward Ng, Cecilia Chan, and Baruch Givoni, "Outdoor thermal comfort study in a sub-tropical climate: a longitudinal study based in Hong Kong," *International Journal of Biometeorology,* vol. 56 (1), pp. 43–56, 2012.

Johansson, Erik and Rohinton Emmanuel, "The influence of urban design on outdoor thermal comfort in the hot, humid city of Colombo, Sri Lanka," *International Journal of Biometeorology,* vol. 51 (2), pp. 119–133, 2006.

Krüger, Eduardo, Patricia Drach, Rohinton Emmanuel, and Oscar Corbella, "Urban heat island and differences in outdoor comfort levels in Glasgow, UK," *Theoretical and Applied Climatology,* vol. 112 (1–2), pp. 127–141, 2013.

Höppe, Peter, "Aspects of human biometerology in past, present and future," *International Journal of Biometeorology,* vol. 40 (1), pp. 19–23, 1997.

Shuo, Liu, Zhou Guomo, and Mo Lufeng, "The green space monitoring system based on Wireless Sensor Network," in *Education Technology and Computer (ICETC), 2010 2nd International Conference on*, 2010, pp. V5–180–V5–183.

Gaffin, Stuart R., Reza Khanbilvardi, and Cynthia Rosenzweig, "Development of a Green Roof Environmental Monitoring and Meteorological Network in New York City," *Sensors,* vol. 9 pp. 2647–2660, 2009.

Cohen, Pninit and Oded Potchter, "Daily and Seasonal Air Quality Characteristics of Urban Parks in the Mediterranean City of Tel Aviv," presented at the CLIMAQS Workshop, Antwerp, Belgium, 2010.

Gillette, Bill, "*Pollution and UV Damage*", The Centre for Dermatologic Surgery, Last Update: 2011, http://blogs.cooperhealth.org/drlawrence/2011/03/pollution-and-uv-damage/
Holick, Michael F., *et al.*, "Evaluation, Treatment, and Prevention of Vitamin D Deficiency: an Endocrine Society Clinical Practice Guideline," *Journal of Clinical Endocrinology & Metabolism,* vol. 96 (7), pp. 1911–1930, 2011.
SunSignal Sensors, "How It Works", http://sunsignals.com/how-it-works/, 2013.
UVSunSense. "*UVSense Wristbands*," Last Update: 2013, http://www.uvsunsense.com/uvss/
Biosense. "*High quality personal dosimetry*," Last Update: 2013, http://www.biosense.de/home-e.html
ICEPURE. "*ICEPURE: The impact of climatic and environmental factors on personal ultraviolet radiation exposure and human health*," Last Update: 2009, http://icepure.eu/WP_descriptions.html
Lamkin, Paul. "*DoCoMo breath testing smart jacket pictures and hands-on*," Last Update: October 7th 2011, http://www.pocket-lint.com/news/112373-docomo-breath-testing-hands-on
Fahrni, Thomas, Michael Kuhn, Philipp Sommer, Roger Wattenhofer, and Samuel Welten, "Sundroid: Solar Radiation Awareness with Smartphones," in *13th International Conference on Ubiquitous Computing (Ubicomp '11)*, Beijing, China, 2011, pp. 365–374.
MIT Mobile Experience Laboratory, "Mobile UV Monitor", http://mobile.mit.edu/portfolio/mobile-uv-monitor/, 2011.
Igoe, Damien, Alfio Parisi, and Brad Carter, "Characterization of a Smartphone Camera's Response to Ultraviolet A Radiation," *Photochemistry and Photobiology,* vol. 89 (1), pp. 215–218, 2013.
Carnegie-Mellon. "*WaterBot*," Last Update: 2013, http://waterbot.org/
Kimmel, Danielle W., Gabriel LeBlanc, Mika E. Meschievitz, and David E. Cliffel, "Electrochemical Sensors and Biosensors," *Analytical Chemistry,* vol. 84 pp. 685–707, 2011.
Lagarde, Florence and Nicole Jaffrezic-Renault, "Cell-based electrochemical biosensors for water quality assessment," *Analytical and Bioanalytical Chemistry,* vol. 400 (4), pp. 947–964, 2011.
Jang, Am, Zhiwei Zou, Kang Kug Lee, Chong H Ahn, and Paul L Bishop, "State-of-the-art lab chip sensors for environmental water monitoring," *Measurement Science and Technology,* vol. 22 (3), 2011.
Rassaei, Liza, *et al.*, "Nanoparticles in electrochemical sensors for environmental monitoring," *TrAC Trends in Analytical Chemistry,* vol. 30 (11), pp. 1704–1715, 2011.
Namour, Philippe, Mathieu Lepot, and Nicole Jaffrezic-Renault, "Recent Trends in Monitoring of European Water Framework Directive Priority Substances Using Micro-Sensors: A 2007–2009 Review," *Sensors,* vol. 10 pp. 7947–7978, 2010.
IBM. "*IBM Aims to Help Alleviate Water Shortages in Northern California's Wine Country*," Last Update: June 25th 2010, http://www-03.ibm.com/press/us/en/pressrelease/31995.wss
Becaon Institute, "Beacon Institute and IBM Team to Pioneer River Observatory Network", http://bire.org/institute/ibm.php, 2007.
Percifield, Leif. "*dontflush.me*," Last Update: 30th October, 2012, http://dontflush.me/about
Kramer, Herbert J. "*Argo (Data Collection in the Global Oceans)*," Last Update: 2013, http://www.eoportal.org/directory/pres_ArgoDataCollectionintheGlobalOceans.html
EPA. "*Microbial (Pathogen)*," Last Update: November 2nd 2012, http://water.epa.gov/scitech/swguidance/standards/criteria/health/microbial/index.cfm
Insta-Link, "Get Started with an Advanced SmartScan™ Kit", http://insta-link.com/poolspa/learn_morehome.html?tab=2#tabbedpanels1, 2012.
Edgar, Tricia. "*Smartphones to Determine Water Quality*," Last Update: June 4th 2013, http://www.kalev.com/clean-water-from-the-cloud-mobosens-uses-smartphone-technology-to-determine-water-quality/
Maisonneuve, Nicolas, Matthias Stevens, Maria E. Niessen, Peter Hanappe, and Luc Steels, "Citizen noise pollution monitoring," presented at the Proceedings of the 10th Annual International Conference on Digital Government Research: Social Networks: Making Connections between Citizens, Data and Government, 2009.
Rana, Rajib Kumar, Chun Tung Chou, Salil S. Kanhere, Nirupama Bulusu, and Wen Hu, "Ear-phone: an end-to-end participatory urban noise mapping system," presented at the Proceedings of the 9th ACM/IEEE International Conference on Information Processing in Sensor Networks, Stockholm, Sweden, 2010.
Kanjo, Eiman, "NoiseSPY: A Real-Time Mobile Phone Platform for Urban Noise Monitoring and Mapping," *Mob. Netw. Appl.,* vol. 15 (4), pp. 562–574, 2010.
Bergner, Benjamin, Jan-Philipp Exner, Peter Zeile, and Martin Rumberg, "Sensing the City – How to identify Recreational Benefits of Urban Green Areas with the Help of Sensor Technology," presented at the RealCORP, Vienna, 2012.
Martí, IreneGarcia, *et al.*, "Mobile Application for Noise Pollution Monitoring through Gamification Techniques," in *Entertainment Computing - ICEC 2012*. vol. 7522, Herrlich, Marc, Rainer Malaka, and Maic Masuch, Eds., Springer Berlin Heidelberg, 2012, pp. 562–571.
EPA. "*Radon - Health Risks*," Last Update: March 19th, 2013, http://www.epa.gov/radon/healthrisks.html

Boyd, Mark. "*Sensors Monitor Radiation in Japan - Engineers give data to the people*," Last Update: May 1st 2011, http://www.deskeng.com/articles/aabawh.html

Safecast, "*Safevcast - A Global Sensor Network Collecting and Sharing Radiation Measurements*", Last Update: 2013, http://blog.safecast.org/about/

Lawrence, Dune. "*China Says Sanlu Milk Likely Contaminated by Melamin*," Last Update: September 12th 2008, http://www.bloomberg.com/apps/news?pid=newsarchive&sid=at6LcKJB6YA8

Isakovic, Alja, "*An important milestone for CubeSensors: the Summer batch sold out in just a month!*", CUBESENSORSBLOG, Last Update: April 16th 2013, http://blog.cubesensors.com/2013/04/an-important-milestone-for-cubesensors-the-summer-batch-sold-out-in-a-month/

Johannesen, Hanne-Louise. "*Pollution sensoring and visualizing garment (CO2-dress)*," Last Update: December 15th 2009, http://www.fashioningtech.com/photo/album/show?id=2095467%3AAlbum%3A12419

Chua, Jasmin Malik. "*Dahea Sun's Cabbage-Dyed Dresses Change Color to Indicate Rain's pH*," Last Update: June 27th 2012, http://www.ecouterre.com/dahea-suns-cabbage-dyed-dresses-change-color-to-indicate-rains-ph/

Lees, Kathleen. "*World Water Day: 3.4 Million People Die Each Year from Water, Sanitation, and Hygiene-Related Causes*," Last Update: March 23rd 2013, http://www.scienceworldreport.com/articles/5756/20130323/world-water-day-3-4-million-people-die-each-year.html

Banna, Muinul H., *et al.*, "Online drinking water quality monitoring: review on available and emerging technologies," *Critical Reviews in Environmental Science and Technology,* pp. null-null, 2013.

Pellerin, Brian A., *et al.*, "Assessing the sources and magnitude of diurnal nitrate variability in the San Joaquin River (California) with an in situ optical nitrate sensor and dual nitrate isotopes," *Freshwater Biology,* vol. 54 (2), pp. 376–387, 2009.

Corke, P., *et al.*, "Environmental Wireless Sensor Networks," *Proceedings of the IEEE,* vol. 98 (11), pp. 1903–1917, 2010.