Methods to Advance Climate Science in Respiratory Health

Satellite-Based Environmental Modeling for Temperature Exposure Assessment in Epidemiological Studies

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KEYWORDS

• Environmental modeling • Air temperature • Ambient temperature
• Environmental epidemiology • Public health • Remote sensing

KEY POINTS

- Earth observation data allow the advancement of exposure assessment in temperature modeling for climate science.
- Spatiotemporally resolved air temperature at the residence resolution can reduce exposure bias in estimated health effects and improve our understanding of human adaptation to temperature.
- Extremes in high or low temperature are associated with adverse respiratory outcomes.
- Temperature can enhance the impacts of ambient air pollution on respiratory outcomes.

BACKGROUND

Scientific consensus strongly supports the scenario that greenhouse gas emissions and air pollution generated by human activity are changing the global climate.[1] This change in climate will lead to warmer air temperature and more extreme weather events with greater heat stress, which in turn are associated with increased morbidity

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and mortality. The global average air temperatures are predicted to increase between 1.4°C and 4.4°C by the year 2100 with respect to the temperature from 1850 to 1900.[2] The ongoing climate change is attributed to the impacts of population growth and increased consumption.[3] Although climate change is widely accepted by the scientific community and many governments,[4] the extent of its impacts are still unclear. Understanding the direct effects of climate change on human health will inform more refined policies to protect the health of communities and populations across the globe.

Epidemiological studies have described a substantial increase in morbidity and mortality in conjunction with heat episodes,[5] of which the 2003 heat wave in Europe is a well-known example.[6] Heat stress may be additionally exacerbated by the urban heat island (UHI), which is a localized anthropogenic climate modification in the urban atmosphere, especially in the urban canopy layer where most human activity occurs[7] and greater respiratory morbidity is also documented. Variable temperatures (such as low, high, and extreme exposures) have been associated with increased morbidity and mortality across varied regions and climates.[8–11] The elderly[12] and children,[13] especially the old and infants, are particularly at risk for a variety of conditions including cardiovascular,[14] cerebrovascular,[12] and respiratory diseases.[12] Heat effects are mostly short term (lag 0–3 days) whereas cold effects lag by up to 30 days.[12] Temperature also affects health through its role in the prevalence and distribution of vector-borne and infectious diseases[15] and its interaction with air pollution.[16]

This review provides an overview of the current state of the art methods for estimating air temperature from earth observing satellite data and its application in environmental health studies. The first sections of the review "*Exposure misclassification*," "*Traditional modeling of air pollution*," "*Hybrid modeling, incorporating earth observation data into temperature exposure modeling*," and "*Estimating air temperature from land surface temperature*" describe how land surface temperature (LST) is used to derive air temperature (Ta) for health studies. "*Satellite-derived air temperature and respiratory outcomes in environmental health studies*" and "*Air temperature enhanced the effects of air pollution on respiratory outcomes*" summarize recent epidemiological studies using these generated Ta predictions for investigating adverse health outcomes focusing on respiratory outcomes related to temperature exposures.

EXPOSURE MISCLASSIFICATION

Until recent years, environmental health studies on the association between temperature and human health have traditionally estimated exposures for an entire city or across countries based on the air temperature (also known as ambient temperature or near-surface temperature) measured at one or a few monitoring stations that is available close to the residence. Although most of these studies focus on urban areas, where the bulk of the population is found, even the nearest station could be several kilometers away. The study populations might even be exposed to a different microclimate due to fine scale intra-urban gradients, potentially biasing the health effect risk estimates due to exposure measurement error (also known as exposure bias or exposure misclassification, ie, assigning inaccurate exposure to each study participant)[17] which may result in a downward bias in estimated health effects. Thus, development of better exposure assessment methods were critical to handle available health outcome datasets, which are often misaligned in both time and space.

TRADITIONAL MODELING OF TEMPERATURE

To address this issue of exposure misclassification, researchers have explored a multitude of methods to produce spatially continuous high-resolution temperature surfaces for use in the fields of public health, meteorology, climatology, hydrology, and ecology. Techniques have varied in complexity from simple interpolations to advanced downscaling models.[18] Many groups in the last decade have explored the use of advanced statistics and geospatial models such as advance linear mixed models, complex space–time interpolations, and land use regression methods.[19–21] These models while improving upon early efforts for spatial temperature variations are still limited in their temporal extent and are inadequate for capturing daily and intra-daily temperature variations.

HYBRID MODELING: INCORPORATING EARTH OBSERVATION DATA INTO TEMPERATURE EXPOSURE MODELING

Access to large administrative databases (eg, NASA satellite data) obtained via satellite remote sensing make it possible to efficiently collect and use climate and weather-related data to facilitate place-based respiratory health research. Earth observation data (from orbiting satellites) provide us with land skin temperature or LST data, which are derived from measured thermal radiation using Planck's law and adjusting for atmospheric effects and surface emissivity.[22] LST is used as a proxy for air temperature, and thus multiple groups have explored the use of LST to model ground level air temperature (Ta). The broad spatial coverage enabled by these satellites allows us to expand exposure data far beyond the range of conventional ground monitoring networks to penetrate rural and suburban areas. This greatly enhances our ability to estimate subject-specific exposures at place of residence and robustly reconstruct the spatial and temporal patterns of temperature exposure.[23–26]

One of the most widely used instruments for measuring LST is the moderate resolution imaging spectroradiometer (MODIS) carried by the Terra and Aqua satellites. MODIS has a 1 km spatial resolution LST product, and each satellite passes twice daily (equator crossing at 10:30 and 22:30 for Terra; 13:30 and 1:30 for Aqua). This results in a total of 4 MODIS measurements per day. Terra was launched in December 1999 and Aqua followed in May 2002. A validated higher-level (pre-calculated) twice daily 1 km LST product is freely available for each satellite.[27] The MODIS instrument's combination of a high temporal resolution (4 measures per day) and moderate spatial resolution (1 km) makes it well suited for many epidemiological studies. The NASA successor for MODIS, the Visible Infrared Imaging Radiometer Suite (VIIRS) is aboard the joint NASA/NOAA Suomi National Polar-orbiting Partnership (Suomi NPP) and NOAA-20 satellites. VIIRS, the successor to the MODIS platform, was launched in 2011 and collects visible and infrared imagery along with global observations of Earth's land, atmosphere, cryosphere, and ocean. It improves upon the spatial resolution of MODIS by providing data at 375 m resolution.[28]

ESTIMATING AIR TEMPERATURE FROM LAND SURFACE TEMPERATURE

Comparing to LST, T_a is a more precise measurement of the temperature that humans are exposed, and T_a is thereby used more often in public health research to investigate the adverse effects of ambient temperature. And as LST and T_a are closely related, studies developed modeling approaches to estimate T_a from LST data. The calibration and conversion between T_a from LST are complex.[29–31] Kloog and colleagues[23] were one of the first groups to develop a method using linear mixed models that explored the day-to-day variation in the LST–T_a relationship and allow for a robust calibration method. This multi-step geo-statistical approach also included a gap-filling stage that estimates T_a for day-locations where LST is unavailable based on information from nearby stations and predicted T_a at the location on days when LST is available.

The method has been later expanded to estimate daily T_a at 1 km resolution across the Northeastern United States (RMSE = 2.2 T_{mean}),[24] the Southeastern United States (RMSE = 1.4 T_{mean}),[25] France (RMSE = 1.7 T_{mean}),[26] and Israel (RMSE = 0.9 T_{mean}).[32]

Oyler and colleagues[33] presented a novel statistical framework for producing 800 m resolution gridded dataset of daily minimum and maximum temperature for an unprecedented period between 1948 and 2012 for the conterminous United States. They use weather station data and elevation-based predictors of temperature, while also implementing a unique spatiotemporal interpolation that incorporates remotely sensed 1 km LST temperature. The framework is able to capture several complex topo-climatic variations, including minimum temperature inversions, and represent spatial uncertainty in interpolated normal temperatures. They present excellent performance with mean absolute errors for annual normal minimum and maximum temperature of 0.78°C and 0.56°C, respectively.

New approaches in more recent studies have applied new machine learning methods to predict daily air temperature. Hough and colleagues[34] have modeled daily air temperature from 2000 to 2016 at a base resolution of 1 km^2 across continental France and at a 200 × 200 m^2 resolution across large urban areas. They predicted 3 Ta measures: minimum (T_{min}), mean (T_{mean}), and maximum (T_{max}). They calibrated daily Ta observations from weather stations with remotely sensed MODIS LST and other spatial predictors (eg, normalized difference vegetation index [NDVI], elevation) on a 1 km^2 grid. To increase the spatial resolution across large urban areas, they trained both random forest and extreme gradient boosting models to predict Ta predictions on a 200 × 200 m^2 grid. They used a generalized additive model (GAM) to ensemble the random forest and extreme gradient boosting predictions with weights that vary spatially and by the magnitude of the predicted residual. Model performance was excellent with RMSEs of 1.9°C, 1.3°C, and 1.8°C (T_{min}, T_{mean}, and T_{max}, respectively).

Jin and colleagues[35] applied a 3 stage ensemble model to estimate daily mean Ta from satellite-based LST over Sweden during 2001 to 2019 at a high spatial resolution of 1 × 1 km^2. The ensemble model incorporated 4 base models, including a GAM, a generalized additive mixed model, and 2 machine learning models (random forest and extreme gradient boosting), and allowed the weights for each model to vary over space, with the best-performing model for each grid cell assigned the highest weight. They included additional variables such as land cover type, NDVI, and elevation. Model performance was good and comparable to other machine-based exposure models with a RMSE of 1.38°C.

Flückiger and colleagues[36] applied a 2 stage approach using random forest to impute missing MODIS LST at a 1 × 1 km resolution and used this the gap-filled MODIS data to explain spatiotemporal variation in the measured ground-based air temperature data at a 100 × 100 m resolution across Switzerland. They used a range of predictor variables, including meteorological parameters, NDVI, impervious surface, and altitude. Their models managed to capture temporal and spatial variations in air temperature in Switzerland from 2003 to 2018 at a fine spatial resolution of 100 × 100 m. The models showed excellent performance with yearly RMSE ranging from 0.94°C to 1.86°C, respectively. They were also able to capture the UHI effect and some typical weather phenomena caused by Switzerland's complex topography.

Fig. 1 summarizes the general process common in many of the above-mentioned new modeling approaches. This starts with the geospatial collection of data (monitor data, satellite data, and all spatial and temporal variables). This is followed by a calibration stage, where the monitor Ta data are regressed against the satellite LST and all other geo-spatial predictors. Once robust model fits are achieved, the prediction stage

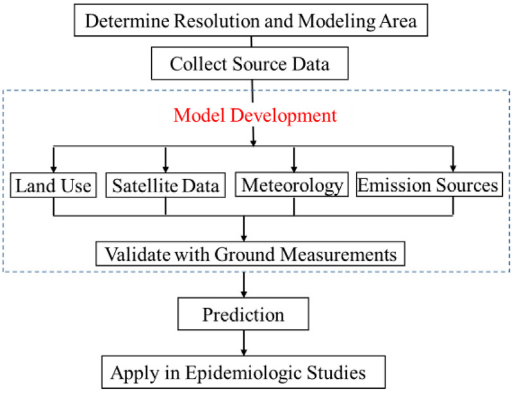

Fig. 1. General modeling process using earth observation data and hybrid modeling approaches.

takes place where new Ta data are generated based on the calibration model fits. All model stages are validated at each step. These final predictions are then distributed to collaborators and used in health outcome studies.

SATELLITE-DERIVED AIR TEMPERATURE AND RESPIRATORY DISEASES OUTCOMES IN ENVIRONMENTAL HEALTH STUDIES

The extreme weather and, in particular, the adverse health effects of ambient air temperature have been gaining both scientific and public interest in recent years. There have been multiple research articles using spatiotemporally resolved temperature data to examine the relationship between air temperature and adverse health outcomes. In this review, we focus on the adverse effect of temperature on respiratory disease outcomes. We divided the current literature into 2 groups based on how temperature was considered: studies using temperature as the main exposure and studies using temperature as an effect modifier.

A growing body of literature has shown that high-temperature exposure increases the risks of respiratory diseases outcomes, such as hospital admissions or incidence or exacerbation of respiratory diseases.[37–39] Studies in recent years leverage modeled temperature data that are increasingly spatiotemporally resolved to understand the adverse respiratory effects of ambient temperature exposure. Using gridded temperature data modeled from both satellite and meteorological models,[40] Danesh-Yazdi and colleagues[41] reported that a warmer cold-season temperature was associated with increased respiratory disease hospitalization (rate difference = 62.13, 95% CI: 51.68, 73.02) in a large sample in the United States. There are also a commonly used gridded temperature data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) that incorporate global satellite data in their models. Although these models are spatially coarse, several studies have used the ECMWF's temperature data and reported associations between air temperature and increased risks of multiple respiratory outcomes, including respiratory disease visits[42,43] and respiratory disease mortality.[44] More recent studies have used high-resolution satellite-based modeled temperature data. For example, using the 1 km resolution temperature data modeled from MODIS satellite.[24] Yitshak-Sade and colleagues[45] reported that both short- and long-term exposure to increased ambient temperature was associated with increased respiratory disease admissions in the

Northeastern United States. Rice and colleagues[46] demonstrated that short-term average temperature exposures were associated with lower lung function. Specifically, these authors found that a 5°C increase of previous-week temperature was associated with a 20 mL lower (−34, −6) forced expiratory volume in 1 second. This effect was more pronounced in cold seasons.

AIR TEMPERATURE ENHANCED THE EFFECTS OF AIR POLLUTION ON RESPIRATORY DISEASES OUTCOMES

Emerging studies have begun investigating the synergistic health effects between these 2 exposures. In a study conducted among a Japanese population, Phosri and colleagues[47] reported strengthened associations between ambient ozone exposure and emergency ambulance dispatches when temperatures were either extremely low or extremely high. Lu and colleagues[48] linked the co-exposure to both high temperature and air pollution (eg, particulate matter with a diameter of ≤10 μm, PM_{10}; sulfur dioxide) with increased risk of asthma in Chinese children. Also in China, Jin and colleagues[49] reported interactions between cold weather and high fine particulate matter with a diameter of less than or equal to 2.5 μm ($PM_{2.5}$) as well as PM_{10} in relationship to increased hospitalizations of childhood asthma. This research team[50] also investigated the modifying effect of $PM_{2.5}$ on the association between temperature variability and childhood asthma hospitalizations, but no significant modifying effect was identified. Evoy and colleagues[51] conducted a panel study for the interactions between $PM_{2.5}$ and dry bulb globe temperature (DBGT) with adult lung function. Although no significant interaction was observed, the association between $PM_{2.5}$ and reduced lung functions became much stronger when DBGT was included in the models. Zhang and colleagues[52] reported that respiratory mortality was increased by 2.67% (95% CI 0.57%, 4.76%) with each 10-μg/m^3 increase in ozone (O_3) when ambient temperature exceeded 28°C. Findings from earlier studies on the interactions between ambient temperature and ambient air pollution have also been summarized in 2 review articles by Areal and colleagues[53] and Annenberg and colleagues.[54] Taken together, research to date indicates that exposure to extreme temperature amplifies the association between ambient air pollution and respiratory diseases. Moreover, this modification effect is seen as both temperature extremes, either the low temperature or the high temperature can pose increased risks of adverse respiratory outcomes.

The underlying mechanisms by which high or low temperatures may exacerbate respiratory diseases are not well understood. Airway inflammation is central to the pathophysiology of respiratory diseases including both asthma and chronic obstructive pulmonary disease[55,56] with several studies demonstrating a link between low air temperature exposure and altered inflammatory biomarkers.[57–60] Owing to the widespread interests of global warming, some studies have also investigated the mechanisms of high temperature on human health. Extremely high temperatures have been linked to increases in acute phase inflammatory biomarkers including increased platelet release and increases in red and white cell counts in circulation as a response to the heat exposure.[61] How changes in these acute phase response indicators are related to respiratory diseases are not clear. Other research suggest that high air temperature may affect the systemic thermoregulation and thereby lead to airway inflammation.[62–64] Besides the direct and acute impact of air temperature on the human body, warming temperatures related to climate change can increase the formation of O_3 and ambient aeroallergens[65] (eg, pollens), further impact respiratory heath.

SUMMARY

Existing and evolving methods increasingly provide highly spatially and temporally resolved exposure data relevant to climate research in respiratory health. This review focuses on an exemplary approach leveraging advances in satellite remote sensing coupled with advanced geospatial modeling approaches to characterize temperature exposures. These new modeling methods and algorithms advance the state of the art in epidemiological studies looking at the respiratory health effects of climate change and increase the number of subjects for which exposure estimates are available globally.

These methods have enabled research that contributes to a growing evidence base linking temperature extremes (hot and cold) with adverse respiratory outcomes. More mechanistic studies are needed to understand the biological underpinnings of these associations. Additionally, studies examining the complex interactions among temperature, air pollution, and aeroallergen exposures are worthy of more exploration to elucidate the fuller scope of climate change effects on respiratory health. Unless strategies are put in place to curb global climate change, we will continue to see upward trends in both acute and chronic respiratory health impacts.

CLINICS CARE POINTS

- The rise in global temperature has led to an increase in heat waves and extreme weather events, which pose serious risks to respiratory health and can lead to worsened symptoms for patients with respiratory diseases.
- Recent advances in open-source earth observations data have allowed for improved exposure assessment through temperature modeling, which can provide clinics with more accurate data to inform clinical decisions.
- Spatio-temporally resolved air temperature data at the residence scale can reduce exposure bias and enhance our understanding of the immediate health consequences associated with ambient temperature, which can inform treatment plans and improve patient outcomes.
- Clinics can play a crucial role in mitigating the effects of climate change on respiratory health by implementing appropriate measures, such as educating patients on how to protect themselves during extreme weather events and high temperature periods.

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DISCLOSURE/CONFLICTS OF INTEREST

There are no conflicts of interest.

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