**Tropical cyclones – Stuff that belongs elsewhere**

*Beginning of point location section*

[BA: Let's think some about the order we want for these sections. We're making

several good points / analysis here. First, we're defining what we mean by the

resolution ("point location" here). We probably want to start with that. Then we

have some examples for studies that have had outcome data at this resolution.

Maybe that could go next, to help illustrate the definition we've given. We've

got some information on \*how\* the data at this scale was collected (e.g.,

geocoding from addresses reported from the study subjects), which I think is

really interesting. Finally, we're got some text that talks about how data at

this resolution could be integrated with some main formats of exposure data. We

might want to end with that (or maybe even, as we work on this draft, that might

go into a different section of the paper).]

*right at the end of point locations section*

[Once we give examples, we should talk about what level the physical exposure data was recorded as. Did it line up exactly? Grided data. Some studies avoid the problem by creating a proxy (ex: dist from the storm track).]

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\*Misclassification error / measurement error.\*

One pathway for problems is through misclassification / measurement error bias. Misclassification error occurs when exposure and outcome variables are measured in categories and the wrong category is assigned to a particular case/observation - for example when a case that is exposed is incorrectly categorized as unexposed. Failure to classify exposure accurately(for example, classifying certain observations as exposed to a storm when they really were not, or vice-versa), allows misclassification bias to move the results of the study further from the true parameter . Measurement error occurs when the variables being measured are continuous, such as the amount of precipitation or the wind speed that was measured during a tropical cyclone.

Environmental epidemiology studies are often prone to misclassification error because the methods of assessing exposure are not always congruent with the way that researchers conduct human impact studies. It is easy to map the path of a tropical cyclone's center, and categorize every county it passes through as an exposed county. However, this information by itself would not give the researcher any information about population centers that the storm passed through or near to. A town within an exposed county may or may not have been close to the storm's path. Conversely,a town in an unexposed county could be located very close to the border of an exposed county, and even be closer to the storm's track than a different town within that exposed county. Where physical exposure data is often collected at point locations, human impact data is often at the level of zip code, county, metropolitan area, or state. It is easy to here how spatially, physical exposure data and human impact data are collected at different resolutions that increase the risk for misclassification error.

Another source of misclassification error in tropical cyclone impact studies is self reported data. Self reported data is used to assess human impacts that are often not known or apparent until after the tropical cyclone event. A great example of this is in [@lieberman2017self] where study subjects were asked to report their own flooding exposure and their mental health symptoms of depression, anxiety, and PTSD. It is reasonable to believe that self perceived exposure to hurricane related flooding would not be independent from perceived negative mental health symptoms and thus potentially contribute to differential misclassification error in this situation.

\*Dichotomizing continuous exposure measurements.\*

Sometimes, researchers use an agreed upon threshold to split a continuous metric into a binary classification (exposed or unexposed). For example, a county may be classified as exposed or unexposed based on local winds exceeding a threshold (e.g. gale-force winds or higher). S.C. Grabich et al. 2016 classified hurricane exposure in a Florida county using maximum wind speed. Maximum wind speed is a continuous variable, but the study used binary categorizations to divide it into tropical wind speeds, classified as greater than 39 miles per hour, and hurricane wind speeds, classified as greater than 74 miles per hour. Florida counties experiencing maximum wind speeds below 39 miles per hour were considered unexposed.

Researchers typically dichotomize or categorize continuous variables in several situations for several reasons. They do this typically because it simplifies the data and allows for easier analysis and interpretation [@naggara2011analysis]. Additionally, it is very common in clinical settings to categorize continuous variables, for example hypertensive or not hypertensive, overweight or not overweight, dead or alive, etc. [@van2008leave].

Despite several advantages to dichotomizing continuous variables that we just discussed, the general consensus in epidemiology is not to do it. Statistical power is lost because so much information is lost when categorization occurs [@van2008leave]. This makes sense when you consider that continuous variables allow you to observe nuance in the data and perceive a dose response relationship between the predictor and response variables, should one exist. This effect is masked when researchers categorize data, and even more so when a smaller number of categorical variables are used (for example dichotomization itself at 2). Generally, if you are going to categorize continuous data, it is better to use 3 or more categories rather than just two, because this will capture more of what the data that would otherwise be lost. An example of a paper that used three different bins was [@kinney2008autism], which explored the risk of autism after a pregnancy that included exposure to a tropical storm in the state of Louisiana. The study authors classified tropical storm exposure as severe, intermediate, and low exposure, and these exposure classifications were determined based on whether a mother lived in a Louisiana parish that had both of the exposure factors of interest: storm intensity and storm vulnerability. Storm vulnerability in this case was based on another dichotomy: whether or not the storm center passed through the parish of interest. Storm vulnerability was a measure of how vulnerable the inhabitants of the parish were to the effects of a storm (higher socioeconomic neighborhoods and parishes have more resources to withstand and recover from a tropical storm for example).

Another obvious problem with categorizing continuous data is that the cutoff points are often arbitrary. In the case of dichotomization, the median is often used, but there is typically no reason to assume that the median is a reasonable cutoff point. Because different samples will have different medians, this automatically makes many categorical bins difficult to compare across studies [@altman2006cost]. Further, choosing optimal cutoff points that give the smallest p-values can lead to spurious results [@altman2006cost].

Not surprisingly, dichotomizing continuous variables can bias results. A study by Selvin showed that the odds ratios can be significantly different depending on the chosen cutoff that is implemented in a study [@van2008leave]. Categorical variables can also put otherwise similar observations into separate bins if they are close but on opposite sides of the cutoff [@altman2006cost]. Choosing a median as a cutoff is intended to delineate bins, but if the bins are a "high" and "low" group, two individual observations that may only be a fraction different, but on either sides of the mean, will be classified as high and low respectively, and give the false impression that they are significantly different.

While dichotomizing continuous variables is something that can be done for either the exposure or the outcome of interest in a study, for our purposes we are primarily interested in continuous \*exposures\*. This means that we are primarily interested in the effects of dichotomizing variables such as wind speed, rainfall, temperature, distance from storm center, and distance from coastline, among other factors. Many epidemiology studies will dichotomize continuous outcome variables such as blood pressure, body weight (BMI), and length of pregnancy in order to gage medical concern and priorities, but because we are concerend with creating a data framework that makes storm exposure data accessible for epidemiologists, exposure scientits, economists, and other scientists to use, we have a priority to look at exposure variables.

\*Scales for Categorizing Wind Speeds\*

There are several methods in existence for categorizing wind speed, one of the most frequently used variables for estimating exposure to hurricanes and tropical storms. The first is the Saffir-Simpson scale, which uses five different bins to classify varying levels of wind speed and determine the severity of a storm. The first level, Category 1 is designated for hurricanes and tropical storms with maximum wind speeds of between 64 - 82 knots and is generally considered dangerous to people, livestock, and pets from the hazard of flying and falling debris [@taylor2010saffir]. On the higher end of the scale, Category 5 designates hurricanes with maximum wind speeds above 137 knots and is considered to have catastrophic effect on damage and a high probability of injury or death to people, livestock, and pets even if they are sheltering indoors [@taylor2010saffir].

Forecasters classify hurricanes into categories on the Saffir-Simpson scale based on maximum sustained surface wind speed. This is defined as the peak one minute wind speed at a height of 10 feet over an unobstructed exposure [@taylor2010saffir]. An important limitation of the Saffir-Simpson scale is that it doesn't account for other hurricane-related impact variables such as storm surges, flooding, and tornadoes [@taylor2010saffir].

Another scale used to categorize wind speed is the Beaufort scale, created by Admiral Sir Francis Beaufort, used to classify wind speeds both over land and sea. While the Saffir-Simpson scale is only designated for wind speeds that are already at hurricane levels (greater than 64 knots), the Beaufort scale considers the wind speeds below this. The scale ranges from Force 0 (0-1 knots and calm) to Force 12 (64 to 71 knots and hurricane). Other interesting parts of the scale include Force 3 (4-6 knots) which is a gentle breeze, and Force 8 (34-40 knots) which is considered a gale.

Categorizing wind speeds presents researchers with some of the same problems mentioned above that happen when dealing with continuous data, but both scales are based off associations between winds at certain speeds and observed damage and health impacts to communities exposed to these wind speeds.

\*Aggregate Hurricane Exposure Metrics\*

Another method of assessing damage and impact of tropical storms and hurricanes is through a single aggegrate exposure metric. While aggregate values often represent the mean of all the values recorded, weather data is typically assessed by the maximum value. This could be something like the maximum wind speed reached in a particular county or parish, or the total monetary cost in damage due to flooding in a metropolitan statistical area. The Saffir-Simpson scale is an example of how entire storms are often classified by their maximum wind speed.

Although using a single exposure value can simplify analysis and interpretation, particularly over an extended temporal scale, there are some obvious drawbacks to relying on one single aggregate value. For example, the Saffir Simpson categories typically correspond only to the geographic point location where the maximum wind speed was observed [@taylor2010saffir]. Hurricane Wilma in 2005 for example, was a Category 3 hurricane when it made landfall on the southwest coast of Florida, but it created Category 1 and Category 2 conditions for the more populous Miami-Dade, Broward, and Palm Beach counties when it finally reached them [@taylor2010saffir].

Single exposure metrics are often used after a storm event has happened. They are very common in assessing ecological damage after a large hurricane.

\*Ecological Bias/The Ecological Fallacy\*

Because studying tropical storm and hurricane exposures requires us to look at different spatial scales, we run the risk of encountering the ecological bias when looking at larger spatial aggregations. Ecological bias occurs whenever the aggregate association between an exposure and an outcome does not properly reflect the association on the individual level [@greenland1989ecological]. Ecological studies themselves don't look at individuals, but rather at an aggregate value, usually within a defined geographic region. Looking at national levels of obesity, cancer, or life expectancy, and comparing countries with respect to these outcomes and some exposure is an example of what ecological studies aim to achieve.

An example of a study that could be prone to this kind of bias is [@kinney2008autism] where Louisiana parishes were considered vulnerable to hurricane exposure based on whether or not the storm center passed through that parish. It is possible that the cases considered exposed based on living in these parishes were not in fact exposed since the storm may have passed through only a certain part of the parish. Never the less, all cases in a parish are considered exposed or unexposed in the aggregate.

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[BA: I'm adding some additional text/notes we can work into Claim 2 as

appropriate. I drafted these while working on another manuscript but they

were more detailed than we needed there, so we can work them in here.]

Measurement error can be either random or systematic. Systematic error can often

be corrected with adjustment if the direction and typical size of the error is

understood. Random error cannot in the same way. Either type of measurement

error can be either differential (associated with the probability of the

outcome) or non-differential (independent of the distribution / probability of

the outcome). In simpler models, this characteristic might help in predicting

whether the resulting bias is likely toward the null; however, more complex

models (e.g., statistical models with adjustment for potential confounders) are

trickier to diagnose in terms of the likely implications of differential versus

non-differential measurement error [would need a ref for this].

When a single value of exposure is assigned across an aggregated level (e.g., a

single exposure measurement for a county or ZIP code), it assumes constant

exposure across that area. However, this will typically not be the

case---hazards like storm-associated wind, rain, and flooding can vary in

intensity across these spatial areas. For some hazards, this variation can be

notable. Storm surge, for example, will typically be limited to coastal areas of

a county or ZIP code. Other hazards, like storm-associated wind and rain, are

more likely to be more homogeneous across space, and so have less

within-county/ZIP code variation. The rainfields for tropical cyclones are very

large, and while there are rainbands within the storm that might have

particularly high rates of precipitation, these progress over the course of the

storm, and it is unlikely that a county will have one area that experienced very

extreme precipitation while another experienced very little [BA: We could see if

we could find a good ref. or two on this point]. Similarly, while topographic

features and other variability can create variation in the sustained and gust

windspeeds experienced in an area from a storm, it is unlikely that one part of

a county would experience high-impact winds from a storm while other parts of

the county experienced mild wind [BA: We could look for a ref for this, too].

If you use a single exposure estimate for everyone in an area, there is the

chance that some people within that area will be misclassified (if exposure is

measured as exposed/unexposed) or have exposure measured with error (if a

continuous metric of exposure is being used), unless the exposure is perfectly

homogeneous across the area. This exposure misclassification or measurement

error can lower the power of the study to detect a clear association between

exposure to a storm hazard and a certain societal impact, as this smoothing

drops information inherent in the within-county variation in exposure levels. It

can also bias estimates of the association between exposure and outcome in the

same way exposure misclassification through any other mechanism would.

When a proxy exposure estimate (e.g., county-level average exposure level) is

used for a group of individuals in the study, it can result in a type of

exposure measurement error called Berkson error. In this case, the true

exposure of each individual is randomly distributed around the proxy or

mean exposure level assigned to him or her. In other words, the group as a

whole is assigned a common exposure level, based on the average exposure

across that group, when in fact the individuals' true exposure levels are

randomly distributed around this common assigned exposure level. [BA: I think

this type of error might be a risk when aggregating exposure data, but we should

look into it a bit more to make sure I'm right.]

It can be important to think about the scale at which the process happens. For

something very local (e.g., aggregating to a very small neighborhood scale),

much less information will be lost compared to aggregated to a large scale

(e.g., state). If an exposure tends to be fairly homogenous across the spatial

scale used for aggregation, then these concerns are lessened

[@wakefield2008overcoming].

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Data that are aggregated across a spatial area---for example, the total number

of deaths in a geographic area in a certain time period---is known as ecological

data, aggregate data, or contextual-level data. Studies that use such data are

known as ecological studies [@sedgwick2014ecological].

Aggregated or ecological data can be used to infer a contextual effect, for

example. Sometimes, however, aggregated data are used to infer individual-level

associations. While the first type of inference seeks to answer questions like

how the county-wide rate of an outcome of interest changes when the county is

exposed to a storm hazard, the second seeks to determine how a person's

individual risk of an outcome changes if he or she is personally exposed to the

hazard. The second type of inference can be prone to bias that results from

cross-level inference---the data used to model the association is at the

contextual level (e.g., county-level) while the inference is for the individual

association between exposure and outcome. When an individual-level association

is estimated from ecological data, the estimate can be very biased from the true

association, event to the point of reversing the effect estimate---estimating a

protective effect, for example, when the true effect is detrimental

[@wakefield2008overcoming]. This type of bias is called ecological or

cross-level bias [@greenland1994invited; @idrovo2011three], and the

misconception that associations estimated from data at the ecological/aggregated

level provide an unbiased estimate of individual-level associations between

exposure and risk of the outcome is called the ecological fallacy

[@wakefield2006health; @portnov2007ecological].

Ecological bias can result both from individual-level exposure measurement error

inherent in assigning a common exposure estimate to everyone in an area, while

the exposure varies in intensity across that area. It can also result from

confounding, even if the confounders are controlled at the ecological level.

When data are aggregated across a spatial area, information is lost about how

all relevant factors---exposure level, outcome risk, confounders, and even

potential effect modifiers---vary within that spatial area. Just as aggregation

smooths over within-area variation in exposure levels, it also smooths over

within-area variation in levels of potential confounders. Depending on the

patterns of this within-area variation, a result could be that ecological-level

control of the confounders does not, in fact, control for their role at the

individual level, and so the association inferred at the ecologic level

continues to be confounded by them when inferred to the individual level. In

other words, a factor could still confound the inference of an individual-level

association, even if it is controlled at a population level in an ecological

model. For example, a study of the association between risk of pre-term birth

and tropical cyclone exposure could control for county-level smoking when

modeling county-level storm exposure and county-level rates of pre-term births.

Even with this control, an observed association could result from differences in

individual smoking status, if there is within-county variation in smoking and if

this has a different pattern across people in the county than variation in

exposure from the county-wide exposure estimate.

If individual-level inference is the aim, and population-level data is

available, there are some methods for using it while still aiming to avoid

ecological bias. Indeed, it can be helpful to use population-level data, as it

is often available for a large population, improving the power and precision of

the study [@wakefield2008overcoming; @wakefield2006health]. Further, the level

of exposure might vary a lot more over the population captured with

population-level data compared to the variation that captured in a smaller

sample of individual-level data [@wakefield2008overcoming]. This can contribute

both to statistical power and improve external validity (as the study data will

cover more of the range of exposure that might ever be expected). There are

ways, for example, to supplement population-level data with samples of

individual-level data through two-level, semi-ecologic study designs

[@wakefield2008overcoming]. Other study designs can also be used to leverage

ecological data while minimizing risk from ecological bias. For example,

potential confounders like age distribution and smoking rates vary much less

within a county over time than comparing between counties. Time series-style

study designs, which compare a county to itself over time, therefore allow for

very similar covariate distributions between exposure and non-exposure. This can

help since the mechanism for ecological bias depends on the joint distribution

between individual exposure, outcome, and covariates, if any are included in the

model. Other studies add to this design by stabilizing for temporal confounding

through the addition of counties that were never exposed, allowing for a

differences-in-differences style approach to calibrate for seasonal or

longer-term trends that might otherwise create confounding. For example, many

health outcomes have a strong seasonal trend, with peak rates in the winter and

lows in the summer. Since the hurricane season stretches from summer into fall,

a study design that compares the rate of a health outcome in an exposed county

to the rate two weeks before the exposure might be biased away from the null,

since baseline rates of the health outcome will typically be moving up over most

of the hurricane season.

Ecological bias can also complicate estimation of effect modification, which

otherwise could help in identifying vulnerabilities and susceptibilities among

certain subpopulations [@wakefield2008overcoming].

For disasters, there are added nuances. First, in some cases, the ecologic-level

effect (contextual effect) will be directly of interest. For example, public

health planners in a city may be more interested in knowing how a storm hazard

exposure is likely to change city-wide rates of certain outcomes than in how it

would change individual-level risk. In this case, it is appropriate to use of

ecologic-level data, and resulting estimates will not be prone to ecological

bias) [@idrovo2011three; @greenland1994invited], although when inferring

contextual effects from ecologic data without considering individual-level

factors, there is a chance for the \*sociologistic fallacy\* [@idrovo2011three].

[BA: In this last sentence, the cited article is a letter to the editor, and it

in turn is referencing some other papers that more fully define these ideas. If

we keep this, we should go back and read more deeply into those cited papers

from the @idrovo2011three reference].

Second, for a disaster, the relevant exposure might be not just at the individual level

(e.g., winds or flooding at the individual's residence), but also throughout a

broader area surrounding the individual. Disasters bring physical hazards that

can harm people directly, but also through indirect pathways. The causal

pathways for tropical cyclones to affect human health and cause other societal

impacts therefore differ from those for a dangerous substance, like air

pollutants, in which the substance itself must enter the body to cause harm.

While some health risk comes directly from the storm (e.g., deaths and injuries

from trees falling on homes or drowning from flooding), there are many more

pathways that are indirect. These include pathways that go through the way that

the storm's damage affects community infrastructure and access to medical care.

For example, a tropical cyclone can bring high winds that cause power outages,

and as a result those affected could be exposed to more outdoor hazards (outdoor

air pollution, heat), struggle to safely store perishable food and medications,

and lose means to power medical equipment. While extreme winds at a person's

residence would increase their risk of a power outage, outages could also be

caused by damage to the grid in another part of the community. In some cases,

then, the level of exposure in a person's community may be as important in

opening a pathway of risk as exposure at the person's immediate location.

Finally, if the disaster has a large health impact, the health outcome of one

person in the community could affect the risk of the outcome (or other adverse

outcomes) for others. This situation is often only the case for infectious

diseases, where one person with the disease can spread it to others. However, if

the community-wide impact is large enough, it can affect access to and

effectiveness of medical care for everyone in the community. if hospitals in the

community are over capacity or have to evacuate, this could increase health risk

for people in a fairly large "catchment" area for that hospital. This effect has

been seen recently with Covid 19---attempts to "flatten the curve" aim to avoid

moving into a state where a community's health system becomes overwhelmed and

can no longer deliver a typical level of care to those in the community. This

effect could happen with either infectious or non-infectious diseases. Also,

there may be confounders that are relevant at the contextual, rather than

individual level, as well as modifiers. For example, whether the county is

coastal could be a contextual-level confounder and effect modifier. This will

influence whether the county is exposed to that storm or not, since storms

usually weaken rapidly when the center is over land. In terms of confounding

pathways, coastal communities might tend to have lower levels of air pollution,

because sea breezes clear the pollution regularly. They might also be wealthier

on average, since property on or near the beach is desirable. Finally, they

might be better prepared for or more hardened against tropical cyclones at the

community-wide level (e.g., through hardier power infrastructure, more rigorous

building codes, higher likelihood of evacuating in advance of a threatening

storm) compared to nearby inland counties.

When inferring individual-level associations from individual-level data, without

considering an additional role of ecological-level factors, this is known as the

\*psychologistic\* or \*individualistic fallacy\* [@idrovo2011three]. [BA: In this

last sentence, the cited article is a letter to the editor, and it in turn is

referencing some other papers that more fully define these ideas. If we keep

this, we should go back and read more deeply into those cited papers from the

@idrovo2011three reference].

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# Discussion

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# Terms

These are terms we're using right now that we might want to iterate on,

in conjunction with our colleagues on the project, to make sure we have

terms that are precise and consistent across the document:

- \*\*physical exposure data\*\*: By this, we mean things that are measured

about the storm like wind speed, rainfall, measures of flooding, and other

things that might be considered more in the realm of what an atmospheric

scientist or engineer might measure about the storm. We're contrasting

this with data that for human impacts studies on outcomes among humans

(e.g., pregnancy outcomes, economic outcomes like unemployment)

- \*\*resolution\*\*: We're using this right now to talk about spatial and

temporal levels of aggregation. Sometimes, we're using "scales" instead, I

think.

-\*\*misalignment\*\*

-\*\*data integration\*\*

- \*\*maximum sustained wind speed\*\*

- \*\*storm track\*\*

- \*\*precipitation\*\*

- \*\*hazard\*\*

- \*\*tropical cyclone\*\*

- \*\*Atlantic Basin\*\*

- \*\*interpolation\*\*

- \*\*aggregation\*\*

- \*\*

Annual Reviews of Microbiology

Annual Reviews of Statistics

Annualreviews.org < Good for learning about stuff for interdisciplinary work.

[@grabich2016hurricane] was another paper that looked at birth outcomes after tropical storms. The researchers in this case found a positive association between exposure to a hurricane and the risk of a pre-term birth.

[@bevilacqua2020understanding] also found higher levels of PTSD, as well as probable depression and anxiety among residents with a higher Hurricane Exposure Score in Houston, Texas. Displaced Puerto Ricans living in Florida after Hurricane Maria also exhibited higher rates of depression, anxiety, and PTSD[@scaramutti2019mental]. These mental health outcomes were compared to Puerto Ricans living on the island, and the individuals who had migrated reported higher frequencies of mental health problems than those who had not. Displacement after a tropical storms is a common human impact that leads to other mental health effects, as well as economic, social, and environmental effects.

Tropical cyclones often disrupt local economies of coastal communities. For example, in Florida, hurricanes lead to demand shocks in the economy with a positive net effect on earnings and negative net effect on employment - counties directly hit by hurricanes experienced up to 4.35% increases in earnings and 4.76% decreases in employment [@belasen2008hurricanes]. This confusing paradox makes sense when one considers that while hurricanes may wipe out local businesses, the post-hurricane recovery period boosts certain businesses and sectors. New Orleans in the aftermath of Hurricane Katrina is evidence of this. While the city initially experienced the negative effects of a shut down economy, several years after the storm revealed that victims of Hurricane Katrina in New Orleans experienced increased income relative to cities not affected by the storm, perhaps due to a strengthed labor market in post-Katrina New Orleans [@deryugina2018economic]. High costs of rebuilding infrastructure, providing resources to displaced populations, medical bills, and loss of businesses after a tropical storm all drive these economic burdens.

Non-differential misclassification refers to misclassification of either the exposure or the outcome, that is unrelated to the other (Aschengrau and Seage 2013). The effect of misclassifying exposures will often, though not always, bias the results of outcome towards the null (Armstrong 1998). In effect, this will weaken or obscure any associations that are present that the researcher may hope to observe in the data (Armstrong 1998).

Differential misclassification error occurs when the misclassification of the outcome is related to the misclassification of the exposure or vice versa [@aschengrau2013essentials]. While non-differential misclassification often (though not always) has the effect of moving the observed association or parameter towards the null, differential misclassification can move the observation in either direction.

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Spatial and temporal misalignment is a problem that researchers run into when integrating data from human impact studies with physical exposure data. For example, physical exposure data on windspeed may have a very fine resolution, possibly down to seconds or minutes, while data on birth outcomes may be at a temporal scale of weeks or even months.