Welcome to this special seminar being sponsored by the Yale Center on Climate Change in Health.

And it’s a pleasure to welcome Daniel Carrión who is currently a postdoctoral Fellow in Environmental Medicine and Public Health at the Icahn School of Medicine at Mount Sinai. He received his PhD from Columbia Mailman School of Public Health from the Department of Environmental Health Sciences and it was in their Climate and Health Program, which is a really great program that our own Chi Chen has been closely associated with in the past.

So we’re really looking forward to Daniel’s presentation on Climate, Energy and Inequity: from Exposures to Epidemiology.

So, Daniel, welcome.

Thank you so much.

So I’m excited to speak to you all today and just by way of a little bit more introduction, I completed my BA at Ithaca College in 2008, and if you remember 2008, that was right when the global recession happened, so a great time to graduate from college.

So I had two part-time jobs, one where I was working...
actually for the Health Department in Tompkins County

in New York state, and the other one where I was working for the Solid Waste Division where I was doing composting and recycling education and outreach.

I then ended up leaving and going to Hudson River Healthcare, which is a network of federally qualified health centers across New York state, about 25 at the time, where I was helping manage outreach and programming for folks with HIV, folks who were homeless, folks in public housing, and migrant farm workers.

I was concurrently doing my masters in public health and environmental health sciences at New York Medical College.

And then after completing my MPH ended up leaving to go to Columbia university where I started a pipeline program called the Summer Public Health Scholars program, a CDC funded program to increase the diversity of the public health workforce, specifically around health equity.

I then started my PhD as Rob mentioned in the department of environmental health sciences and the climate and health program and completed that in 2019.
And then now at the Icahn School of Medicine as a post-doc. And so I’m excited to tell you about the work that I’ve done in the most recent part of this journey, which I characterize being at this nexus of climate energy and health inequity.

So we all know that energy lies at the source of our climate crisis, societal decisions on where we derive energy, how much we need and what we use it for are all leading to increasing global temperatures that we have been observing and we’ll continue to see.

But we’ve run a dynamic tension here, right? Because energy is fundamental to public health. It’s fundamental for folks to stay healthy, from the energy that we use to cook with, to the energy that we use in the winter to stay warm, to the energy that we use in the summer to stay cool.

And so I’ve been fortunate to work in all three of these spaces, thinking about this, these energy tensions in public health, but for the scope of this talk, I’m going to only tell you about two of them, which is about my work in household energy and air pollution related to cooking.
and then more recently temperature epidemiology from summertime temperatures. So quickly about my dissertation work and household energy and air pollution in low and middle income countries. As background, 3 billion people around the world experience energy poverty, which is characterized by cooking and or heating with wood, dung, charcoal, or other biomass fuels. And although the proportion is decreasing overall the absolute counts are actually increasing and the highest increases are actually in Sub-Saharan Africa. And so this is the stove that you would see in many parts of Sub-Saharan Africa, it’s called the three stone fire, which you might guess because there are three stones that prop up a pot and underneath biomass is combusted. We’re concerned about this because the combustion of that biomass leads to a mixture of compounds collectively referred to as household air pollution. And so that comprises CO2 particulate matter, carbon monoxide,
polycyclic aromatic hydrocarbons amongst others, and both the deforestation associated with biomass harvesting depending on country and the combustion are projected to actually contribute to climate change. And we also know that exposure to household air pollution is associated premature deaths each year, millions of premature deaths each year, the largest proportion from lower respiratory infections. And you might know that lower respiratory infections are actually the leading killer of children under five in lower and middle income countries. And so it’s widely agreed that the solution here is to scale up cleaner cooking alternatives like liquified petroleum, gas, electric, and induction. And in Ghana, as in many other countries, LPG represents the cheapest and most accessible options of the three that I just mentioned because the other two electric and induction requires stable and extensive electricity grids that don’t exist in many parts of the world. But if you’re unfamiliar with this literature,
118 00:06:52.260 --> 00:06:55.125 I would understand if some folks in the audience
119 00:06:55.125 --> 00:06:59.480 are confused at how using a fossil fuel can actually help us
120 00:06:59.480 --> 00:07:00.883 fight climate change.
121 00:07:03.600 --> 00:07:06.330 The atmospheric science behind this is complicated
122 00:07:06.330 --> 00:07:09.160 and outside the scope of my talk today,
123 00:07:09.160 --> 00:07:12.270 but rest assured that the international panel on climate
124 00:07:12.270 --> 00:07:16.110 indicates that activities consistent with the greenhouse gas emission reductions
125 00:07:16.110 --> 00:07:23.020 needed for a warming of 1.5 degrees Celsius
126 00:07:19.380 --> 00:07:24.180 world includes transitions to clean cookstoves
127 00:07:24.180 --> 00:07:28.780 that are gas based or electric based.
128 00:07:33.353 --> 00:07:37.330 And unfortunately, atmosphere projections
129 00:07:37.330 --> 00:07:40.490 that are Ghana-specific are actually unavailable
130 00:07:40.490 --> 00:07:44.950 at the moment, but one done in Cameroon
131 00:07:44.950 --> 00:07:48.960 undergoing a similar LPG transition
132 00:07:48.960 --> 00:07:53.710 shows that there are projected net cooling benefits
133 00:07:53.710 --> 00:07:58.140 of switching to LPG rather than continued use
134 00:07:58.140 --> 00:08:00.370 of biomass fuels.
135 00:08:00.370 --> 00:08:04.321 And so this then represents in many parts of the world
136 00:08:04.321 --> 00:08:06.730 climate mitigation opportunity
137 00:08:06.730 --> 00:08:09.513 with potential health co-benefits.
138 00:08:11.660 --> 00:08:14.910 And so my thesis works set out to try and provide evidence
139 00:08:14.910 --> 00:08:18.030 to support clean cooking efforts.
140 00:08:18.030 --> 00:08:19.540 The relationship between energy,
poverty and disease can be described as a pathway from poverty to energy poverty, which then causes household air pollution, and then the exposure to that household air pollution leads to a whole host of diseases. And there are particularly three parts of this pathway that we can try to interrupt in this relationship between poverty and disease in this context.

So we can focus on making the clean available, which is a moniker from the late Kirk Smith, essentially saying identifying interventions to increase the uptake of clean cookstoves like induction or LPG.

We could interrupt this part of the pathway, which is to make the available clean by identifying ways to reduce exposures from biomass combustion.

And then finally, we can do health research to understand biological pathways for improved treatments or interventions. My work was particularly focused on these two parts of the pathway, and I’ll quickly sum up my dissertation in one slide, which is the first paper.
In my dissertation, I created a new framework to try and understand why recipients of new cookstoves often end up stopping using those cookstoves. We refer to this as stove use discontinuance. Acknowledging that a lot of people who receive new cookstoves end up stopping their use in the longer term, we ended up trying to design an intervention to support a government effort. So the government actually freely distributes LPG stoves in rural areas in Ghana. And so we designed and implemented an intervention to try and increase the long-term use of those stoves. The findings suggest that more fundamental policy changes are actually needed just rather than a simple intervention. And finally understanding biological pathways from data from a cohort study, we used banked nasal swabs from infants of the age of one or less and found that household air pollution is associated with increased presence of bacterial and not viral microbes. And this is important because there's other literature...
that otherwise indicates that household air pollution may be contributing to bacterial forms of pneumonia and not viral forms of pneumonia and so this is trying to understand that ideological pathway a little bit better.

So with that very brief overview of my thesis work, I wanted to spend more time on my current portfolio, which is focused on ambient temperature, temperature epidemiology, and energy insecurity. The motivation here is simple. We’re living it right now. Climate change means that there’s an increased frequency and intensity of extreme heat events and hotter average summers. And we know that those higher temperatures are associated with a whole host of health outcomes from cardiovascular to respiratory, to renal, to even violence and other non-health outcomes, but still very health relevant like educational performance. And there’s also work that shows that increased ambient temperatures are associated with perinatal outcomes like pre-term birth. And there’s an important opportunity here
because temperature epi has been largely focused on older adult populations and so there’s an opportunity to grow the literature thinking about pediatric populations.

So I first want to tell you about a study that we’re wrapping up right now, thinking about the case process over design as a way of studying the relationship between ambient temperature and preterm birth.

And the motivation here is also simple for a public health crowd. That preterm birth is a major health outcome that’s associated with high infant mortality. That’s also one of the most pronounced and persistent racial disparities that we know of, and it not only represents poor health potentially in the immediacy of birth, but also potentially a trajectory of poor health in the long term.

Many of the health outcomes are also health disparities for communities of color. And there’s a growing literature on the relationship between ambient temperature and preterm birth.

One of the initial studies identifying this association was actually from Bosu at all in 2010,
a study based in California using the case crossover study design. So if you’re unfamiliar with the case crossover design, a quick introduction. It’s a case-only study design that compares the case time to control times when the event did not happen. And it’s been widely used in air pollution epidemiology and is increasingly used in temperature epidemiology. It’s a temporal comparison, meaning that it’s comparing the same person to themselves at different time points. And so a real perk there is that then it’s not vulnerable to person level forms of confounding. However, proper control selection is then pivotal for proper inference because you want to make sure that you are controlling for potential temporal confounders and other temporal forms of bias. And a key assumption of this design is that there are no trends in the risk of the outcome over time. And it was actually pointed out in a commentary from that original Bosu paper that I mentioned.
that preterm birth actually violates this assumption. And this should be pretty intuitive to folks in the audience because the risk of birth changes pretty secularly over gestation. And so this is something that we need to think about if we’re using this study design for ambient environmental exposures. However six other studies have employed this study design for preterm birth since 2010, specifically for ambient temperature that we’re aware of. And I’m sure that number is much higher if we also consider air pollution. So that this was a great opportunity for a simulation study. So for those who are unfamiliar, a simulation study are essentially computational experiments where we can test the behavior of our epidemiological studies under controlled circumstances. So first what we do is we create a dataset and then we embed a known association in that dataset. We then test our epidemiological analysis’ ability to recover that association. Then we try to repeat, or we repeat this a thousand times to represent some of the stochasticity of the underlying distribution.
And then we could see if different strategies or specifications of models can actually improve our inference. More specific, what data did I use to do this? Well, LaGuardia Airport has temperature data readily available for download online. So we downloaded LaGuardia temperature data as our exposure data. And then for our health data, we actually downloaded CDC wonder data to create estimates of daily preterm births by gestational age from 20 to 36 weeks. And just as a quick definitional thing, preterm birth is generally a birth that take place before 37 weeks. We got these data for 2007 and 2018 from, and then we created data sets with a range of simulated effects ranging from 0.9 to 1.25. I don’t think anyone thinks that temperature is protective of preterm birth, is protective of preterm birth, but we wanted to see how malleable these models were to different underlying assumptions. And then we do these case crossovers to see how our model does at recovering the simulated effects. We ended up doing this using a time stratified control selection for three different time periods.
So we did it for a two week time stratified, a 28 day time stratified, and a month time stratified. And we limit our case crossover to warm month analyses, which is consistent with other studies in this literature. And again, we do this a thousand times to kind of represent some of that stochasticity of the underlying distribution. So these are the input data that we use. So up here are, is the temperature data from LaGuardia Airport and down here are the estimated number of births on a given day that we used from the CDC wonder database. And this orange region is the warm month time period that we used. So the main result that I’m showing you here is for absolute bias. And so absolute bias is simply the difference between the simulated relative risk with the coefficient that we get from the case crossover in the log scale. And I’m showing you first a relative risk of one, meaning that there’s no association between temperature and preterm birth. And you could see that using all three of these study
designs, we actually get relatively unbiased results.

If we look across the entire range of our embedded effects, we see relatively consistent results where all three of these case control selection designs actually yield relatively unbiased results, with our two-week stratified, yielding the noisiest results characterized here by a wider intercore tile range.

And then when we looked at coverage, so coverage would be the coverage of the 95% confidence intervals. What percentage of the time does the confidence interval actually include the true embedded effect?

And you would hope for a model that that would be consistently 95% of the time.

And indeed we see that these models are relatively stable with approximately 95% at all of these risks embedded.

So this is really important work because this shores up the evidence that we have for the case crossover study design and ambient exposures and preterm birth, which I think is really important.

We ended up doing 24,000 simulations and corresponding
case crossovers, finding that the models are relatively unbiased. And we’re excited about wrapping up this project because we’ve tried to enhance reproducibility of our findings and results by using the targets package in R, which then means that other folks can go and rerun these analyses and can actually swap out different years or regions and their analysis, which aids an extensibility of this analysis. And now we’re actually using the case crossover analysis to think about a national level analysis that we’re doing actually in Mexico and hopefully future studies in the U.S. as well. But much the same way that we’re thinking about epidemiological methods, we’re also thinking about improving our exposure methods. And so here, I want to tell you about a project that we just published on, thinking about a one kilometer hourly air temperature model across the Northeastern United States from Maine to Virginia and this is fusing ground data with satellite remote sensing data. And the inspiration for me here is that there is a small,
but growing literature on temperature disparities,
that temperature is perhaps unevenly experienced
based on race, ethnicity, income,
and other forms of potential vulnerability.
And so one limitation, however,
with some of these past studies is that they either use land
surface temperature, which is remotely sensed
with satellites and related to air temperature,
but not exactly air temperature,
or they use forms of land cover,
and land use that are associated with temperature,
but again, not empirical measures of temperature
and so an opportunity then to try and grow this literature,
thinking about these potential temperature disparities.
So the goal here is to create this one kilometer hourly air temperature model
to be able to produce predictions
between the time period of 2003 to 2019.
So we ended up using national oceanic, atmospheric and atmospheric administration data
for ground stations throughout this region
as our ground truths for air temperature.
And so that’s what’s depicted in red
across our study region.
These are the locations of all of the ground sensors
that we used in our model. We then collected 34 predictors that we thought would help us characterize the spatial and temporal patterns of cooling and heating throughout the day. And the goal here is to be able to create consistent and reliable predictions of air temperature across this region, even in places that we don’t have ground observations. So we tested five different statistical approaches to actually create these predictions and show their differences in performance in our paper. For the sake of time, I’m just going to tell you the punchline, which is that we ended up using the XG boost model for our final predictions. So the XG boost model is a powerful machine learning model that we used and had to adapt to create a spatial temporal predictions. And what we ended up doing was actually comparing our XG boost model to the NLDAS-2 model. So NLDAS-2, if you’re unfamiliar is a NASA product that also gives hourly predictions and it’s what the CDC uses for their heat and health.
tracking system, as well as some of their research. And so we thought that this was an important model to benchmark again.

So these are the predictions from our XG boost model, from the hottest midnight of our data set, July 22nd, 2011. And so you can see across this Northeast region from Virginia to Maine, that we reconstruct a great deal of spatial heterogeneity.

Again, this is for one hour, the highest midnight of our time period. And when we zoom in to a sub region, this, in this case being New York City, we see that we reconstruct a great deal of spatial heterogeneity from the urban heat island effect.

And I should have mentioned earlier, NLDAS-2 is hourly, but it’s actually at a much coarser spatial resolution. So these larger grid cells overlaid our predictions are actually the NLDAS-2 grid cells.

And it’s important to note here that in this one, NLDAS-2 grid cell, you have most of Manhattan, a big chunk of the Bronx and a little bit of Queens.
that would get one prediction for all of that region, with the NLDAS-2 predictions, but we can reconstruct a great deal of heterogeneity within that region. And we think that that then is related to the performance of these models. So these are the root mean squared errors from just 2019 from our XG boost model versus the NLDAS-2 model. So RMSE is a measure of predictive accuracy and the goal is to have lower RMSEs. And so we show that our model has a low RMSE of 1.4 Celsius, whereas the NLDAS-2 model has a RMSE of 2.4 Celsius. When we look across the entire region across all years, we see that the XG boost predictions have one third of the mean squared error of the NLDAS-2 predictions. But given the small literature on temperature disparities, we were curious to see if our model was also associated with a measure of social vulnerability. And so what we decided to do was actually conduct a limited application to look at the relationship between our model
and the NLDAS-2 model with social vulnerability.
So what we did was we used the CDCs social vulnerability
index, which are a composite of 15 census variables,
including socioeconomic status, housing, transportation,
language isolation, amongst other characteristics.
And these are variables that the CDC uses to identify
communities that may need support before, during or after a disaster.
The results from the social vulnerability index are proportional.
It produces measures from zero to one.
And so we decided to use mixed models to associate our XG boost model and the NLDAS model
with social vulnerability to see how they were associated.
We wanted this to be a limited application so we only did it for one hour of one day from that hottest midnight that I showed you earlier.
And here are the results.
So, as I mentioned earlier, the CDC social vulnerability index is a proportional measure.
from zero to one.
And so for a unit increase of the CDC SVI,
we see that the NLDAS-2 model shows an increase
of temperature of 0.18 Celsius.

However, when we look at the XG boost model,
we see that our model has a stronger relationship
with an increase in temperature,
with an average temperature of 0.71 Celsius.
And just to ground that in some places that you might know,
so if we look at New York City,
two boroughs of New York City, Manhattan and the Bronx,
and then we look at two counties in upstate New York,
you would see that the NLDAS-2 model has a very,
very shallow gradient of temperature and social
vulnerability across these temperature predictions.
However, with our XG boost model,
because we reconstruct much more spatial heterogeneity,
we see much more of a strong relationship
with the social vulnerability index.
So with the caveat that this is one hour of one day,
what this implies to us is that there’s potentially exposure
misclassification in coarser models.
And that that exposure misclassification may be differential
by neighborhood vulnerability.
So as a takeaway here, we’ve created highly accurate air temperature predictions that we think are right for application to social science, exposure science, and epidemiological studies. But wait, there’s more, I think that this is a great segue because I’m currently expanding on these questions with work that I’m doing at the moment. And so right now, I want to quickly tell you about work that I have underway to try and explore these disparities further and point to its potential importance for epidemiological methods. And so this is about thinking about residential segregation, air temperature, and circulatory mortality. So for the first part of the analysis, I’ll be looking at exposure disparities, similar to the methods that I just showed you, but with some key differences. So unlike the last analysis, this time I actually want to look at the differences and the predictions by race. We know that we have suggestions from past literature that there are differences in exposure by race and ethnicity and so we want to look at this
by race and ethnicity as well now that we have air temperature predictions. And so what we decided it had to do was we decided to aggregate our models to the census tract level like we did before and then we wanted to see what the differences were potentially in an experienced summer. And so what I did was I wanted to compare are the summertime aggregates so I borrowed from the energy literature and computed cooling degree days. So if you’re unfamiliar with cooling degree days, generally speaking, what it is is measures of how much hotter a day is than a threshold value. Generally in the U.S., the threshold value that’s used is 65 degrees Fahrenheit, or 18.3 degrees Celsius. So, as an example, if today is 67, which I wish that it were, but if it were 67 outside today, that would give us two cooling degree days. And then you repeat that for every other day, and then add up all of those cooling degree days for the summertime values. For now I’m only conducting a comparison of exposure experiences by black and white people,
but in the future, I want to consider more racial groups
to try and characterize these exposure disparities better.
And you can imagine that if we see differences by race,
someone could make an argument that it might be
because different people live in different parts of the region.
So for example, saying that more white folks live in the Northern most parts of the region like Maine
and more black folks live in the Southern most part
of the region like Virginia.
And so we wanted to then make this within county comparison
within geographic compact geographies,
to look at exposure disparities within these
more relevant administrative units.
And so to address that,
we then took a similar approach of comparing tracks
within counties with our predictor variable,
being the proportion of the census tract that was comprised of black folks,
and then using random intercepts and slopes by county
to then get county level comparisons.
On the epidemiological side of things,
you can imagine that getting health data that covers
the entirety of this region is pretty difficult so we use it as an opportunity to get creative.

We, again, access to CDC wonder data and although I'm interested in child health, CDC wonder data has some major limitations if we're thinking about a rarer health outcome like preterm birth.

Data are provided are at very coarse geographies. In this case, data are only provided at the county level, and they're also only provided for course time spans.

And then data that are counts that are below 10 are suppressed for privacy concerns.

So, because CVD mortality is a much more common event, we decided to conduct this analysis with CVD mortality.

There are still however, a fair amount of suppressions of data and so to deal with that, we ended up using a left censored Poisson regression since there would be left censoring for lower counts.

And really one of the things that I'm getting at here is around this question of exposure misclassification.

So for example, in many environmental epidemiology studies, there's oftentimes an analysis that looks at effect
modification by race, often finding higher effect estimates based on race and ethnicity. And while there are sometimes reasons to think that this might be the case, depending on exposure and context, I am often left wondering if it’s potentially a consequence of underlying exposure disparities that our exposure models are not picking up. And so with that inspiration, I ended up doing four different regressions, two regressions for white folks using both exposure models and two regressions for black folks using both regression models or prediction models, I should say. And since this ended up being at the county level, I tried to preserve some of the exposure differences by computing weighted by track level racial composition, aggregated up to the county level. So these are preliminary results just for the year 2019. So this plot is simply looking at the distributions by race across the 13 states including DC. And what we see here is that actually both models appear to reconstruct a temperature disparity between whites and blacks.
However, our XG boost model has a much more smoothed out distribution for black folks.

And when we actually look at the median values experienced, we see that they’re about the same for white folks, but between these two prediction models, we have higher exposures for black folks with our XG boost model.

But this is just looking across the entire region, this isn’t actually of the results from our analysis.

We look to see how these were related to the proportion of black people living inside of a census tract. And we found that a zero to one increase for the proportion was associated with 25 higher cooling degree days for the NLDS to model.

But for the XG boost model, we reconstruct approximately 68 cooling degree days.

And so we think that this is potentially important for reconstructing some of these potential exposure disparities and on the epidemiological side of things, when we do a stratified model for white folks, we see a modest but significant effect.
But when we look at those as effect estimates for black folks, we see much higher effect estimates for both models. However, this is for the NLDAS-2 model with about 1.24 as the effect estimate.

It was mentioned in the slide but I should’ve said it before, these are scaled per 92 cooling degree days or one cooling degree day average increase across our time span. And so for the XG boost model, we see that we get a much lower, still higher than for whites effect estimate of 1.14.

So what this means to me, or implies to me that there is potentially exposure misclassification that can appear in epi models as greater susceptibility. And so I think that there is an opportunity here to think further about these models and what they can lend us for health disparities types of research.

So some next steps here is that I have data for more years than just 2019, so I’m going to include more years in this analysis. We also know that there are exposure disparities...
for other forms of environmental contaminants like ozone or PM2.5.
And so I want to potentially control for these spatial temporal confounders, potentially contributing to these relationships. And then I want to include explicit measures of segregation. So, as I mentioned, I showed the proportion of black folks, but there’s a whole host of literature that actually shows different measures of segregation like the dissimilarities or the index of concentration at the extremes. And I would like to use these as potential predictors in these models. And then finally, I want to analyze these disparities in relation to energy data because I’m interested in studying some quantitative research between energy burden and energy insecurity, which leads me to some of my future directions and opportunities. So if you’re unfamiliar with energy insecurity, this is a relatively new framework that my colleague Diana Hernandez at Columbia has used and described as a framework that outlines the interplay between energy needs, financial constraints, and behavioral adaptations.
So I think a lot of us are familiar with this concept in what’s referred to as the heat or eat dilemma. So the heat or eat dilemma describes the kind of precarious situation that historically poor families have been put in during the winter time, do they keep themselves warm or do they forgo some staples, like a healthy meal, or perhaps they get their heating from some sort of precarious thing. We’ve heard the stories if not done it yourselfs, We’ve heard the stories if not done it yourselves, but I think in a warming climate, we need to start having a conversation on analogous, what I’m coining the heat stroke or go broke dilemma. What does it mean to think about that there are folks who potentially have ACs in their homes, but can’t afford to run those ACs. How do we think about that they may be foregoing other important staples of their lives on the other side of things to cool their homes. And so I think that there’s a real opportunity for climate epidemiology and climate and health research.
And finally, I’m also interested in continuing to integrate the social and environmental determinants of health. So I didn’t attend the society for epidemiologic research conference this year, but I saw on Twitter that one of the big takeaways was a quote from Jay Kaufman, who said that all epidemiology is social epidemiology. And I think that that lends a real opportunity for us to think about borrowing from the social epidemiology literature and also lending our tools to the social epidemiology literature. So we recently just published a paper in Nature Communications where we actually used environmental exposure mixtures methods that were designed for the environmental health sciences, and actually implied it to thinking about neighborhood disadvantage to try and understand some of the infection disparities that we’re seeing in New York city for COVID-19. And so I think that there’s an opportunity here to continue, you know, trade and learn lessons across the different areas of public health.
I'm also conducting a large natality analysis that I mentioned earlier in Mexico and soon hopefully accessing data for also New York state. And we're trying to apply mixtures methods in this context as well thinking about perinatal and climate epidemiology. I also want to continue to expand my own environmental justice lens. I think a lot of focus in environmental health has been on distributive justice, but what does it mean to also think about different forms of environmental justice, like procedural justice or restorative justice in these contexts? And then finally, I'm hoping to get more engaged in community and policy engaged research to try and find climate energy and health leverage points that we can use to create a more health equitable and climate equitable future. So of course this research relies on a ton of folks to help make this possible, so thank you to all of those folks, as well as the funding that has made this all possible. And with that, I will open up for questions. So, yeah, thank you, Daniel, for a very well-presented.
and interesting talk.

I could start with a question.

Well, maybe other people are thinking about theirs,

so you spoke a lot about temperature exposure disparities

and then introduced how energy,

so you have the temperature exposure disparities,

and then on top of that,

you have the people with the highest temperature exposure

having less of an ability to deal with that high temperature

exposure and that part you didn’t address as much,

you know, understand that you can only do so much,

but I’m wondering, you know,

have you thought about ways to measure that,

let’s call it energy insecurity in epidemiologic studies

in order to make that next step?

Yeah, absolutely.

So I’m interested in this in two different ways.

So I think that we could do work to actually collect data

from folks to try and get a better sense,

a better quantitative sense of people’s energy insecurity.

So Diana has developed actually an energy insecurity

screening tool and so it would be great to try

and get that screening tool out there
as part of larger studies so that we can understand
the kind of geographic distribution
of this energy insecurity and trying to overlay that
potentially with what we know about temperature.
So that's on one end.
On the other end, I think the lower hanging fruit
is actually to access energy data.
And so this is something that we're working on right now
actually is to use energy data and pair that with
our temperature predictions to see if we could see
differences in the dose response relationship
between neighborhood temperature
and energy utilization by neighborhood.
And if we see differences in the slopes
between those neighborhoods,
then that would imply to me that potentially
those are differences in your response
to the temperature and your ability to keep yourself cool.
Of course, that needs to be adjusted
for many, many different things,
but that is where I'm thinking as a lower hanging fruit
using administrative data at the moment.
Great, other questions, comments?
I have a question or a comment and observation,

first of all, this is an amazing presentation.

It’s brilliant work, and it could not be more timely.

And I’m going to go to your last point, talking about,

you know, the application of your work and of this research

within the current policy development work

at the federal level right now.

And I think that you’re diving in and focusing in

on that exposure data and how

we’re not getting an accurate indication of what

the risk are is vitally important

and there are a couple of proceedings right now, you know,

with the executive order 13895,

with executive order 14009.

There’s an OMB, a docket open until July six.

There’s another FEMA docket open until July 21st,

is how are you, whether you are planning

or whether you could consider

taking your research and getting it into these

and other dockets because that is setting

the administrative record where we can start changing how

the federal government is thinking about this.

So I don’t know what your thoughts are in trying to move
in those spaces.

Yeah, no, absolutely.

And I would definitely look to others who are closer to the policy landscape to help me figure out what the leverage points are. The most proximal leverage point that I’m aware of is actually what environmental justice folks are talking about right now. Folks that We Act are talking about that the low income home energy assistance program has been historically used for helping to keep folks warm during the winter, but has been lesser so used to help keep folks cool during the summer. And so we already have a policy instrument in place to identify the people who need the help, but we don’t have the dollars allocated to the right part, potentially the right part of the exposure distribution. And so I think that that is the most proximal policy instrument that I’m aware of that could help move the needle towards improving public health.

That’s fantastic.

You know I would also throw out taking that as that illustration applying the national environmental
policy act and the resurgence and undoing what the Trump administration did to that law because I think there’s some opportunities for programmatic environmental impact statement reviews and it would be great to get your data, you know, forming the basis of some of those types of actions. So thank you.

Yeah, thank you.

Other questions or comments?

Maybe just a small technical question.

We know that using CDC wonder data for especially the birth outcome, this issue is you mentioned briefly that the temporary resolution is not good enough. They don’t accurate give you the exact date. So I’m wondering how do you deal with in your time cross data with that? Oh yeah, for sure.

So we ended up doing a lot of interpolation estimates. So for example CDC wonder can give you how many births there on it are in a day of the week, in a typical day of the week. And it’ll give you how many births there were in a month. And so we ended up then doing a lot of averaging.
Knowing Tuesdays, let’s say are where, you know, 30% of the births are happening, 20% are happening on Wednesdays, let’s say. Using that relationship, again with the longer month time span to then do a lot of smoothing and averaging to get an estimate of how many births there were. I don’t think for this study we need an actual accurate number because at the end of the day, you’re creating your truth with the simulation methods. It’s just a way of making sure that we have good representation of the different age groupings of different preterm births. Are there more 20 week olds perhaps being born in February rather than in June, right? Trying to preserve some of those distributions of the different weeks of gestation where we spent a lot of our attention. Thanks yeah, that’s makes a lot of sense. And I’m more thinking of like a new addition to your similar study in the future, your future work, if you want to extend to the whole U.S. that might be something to be carefully dealt with. Yeah, absolutely.
So I, there’s a question in the chat.

I think this’ll be the last question. It’s from Taiwo Bello.

Please, how convinced are you about these studies considering that Africa has the hottest temperature and majority had no cooling systems in place and what are the limitations of your research findings?

Thank you.

Yeah, absolutely.

So I think the temperature epidemiology generally shows that there is such a thing as acclimatization, that there are differences in people’s response to different temperatures in different parts of the world based on what they’re historically exposed to.

And so to some degree,

people are climatized to the places that they live in.

Another factor that needs to be considered as well is that humidity is also very different in different parts of the world. So in Western Africa, for example, at least the places that I’ve done research, humidity is not as high as it is in the Caribbean, let’s say, or in other parts of the world, right? And so humidity plays a big part in our ability...
to thermo regulate in our ability to dissipate heat.

And so I think that that’s an important part of this relationship that a lot of temperature epidemiology kind of grapples with to do this. And I think the last thing I should mention is I think we don’t have sufficient evidence in many parts of the world to necessarily say that heat is an issue in Africa, even though the dose response relationships may be different, but nonetheless people are impacted by heat in Sub-Saharan Africa as well and I think it’s actually a call for more research in the region to understand what those relationships look like.

You gave a very interesting talk and congratulations on doing such great work.

Thank you so much.

Okay, take care, everyone.