* Causal Mediation Effects (CMEs) analysis has proven to be an effective methodology to understand potential mechanisms for causal analysis, particularly in the social sciences.   What are the principal limitations of this approach? Is there any advantage of taking a Bayesian approach to learning causal mediation effects?  Finally, can you imagine a scenario where CMEs could be used to address mechanism associated with anthropogenic climate change causes of increased hurricane intensity?

Comprehensive Exam Answers: Chris Wikle

What are the limitations of Causal Mediational Effects analysis?

While Causal Mediational Effects (CMEs) analysis has proven to be an effective methodology for understanding the mechanisms behind causal outcomes, with large historical use in the social sciences, there are significant limitations to note with regards to this approach. CME analysis has had a broad history, and there have been a great deal of methodological change over time. We will address some of the limitations to various methodologies in CME and put forward what we believe to be the best and least limited contemporary execution for CME analysis as well.

MacKinnon, Lockwood, Hoffman, West, and Sheets (2002) put forth a summary of some of the various methods of mediational analysis, with the interpretation of validity under the broader perspective of an intervening variable effect. MacKinnon and colleagues define this as when “An intervening variable transmits the effect of an independent variable to a dependent variable”. While this can be a mediational hypothesis, other non-mediational structures exist wherein an intervening variable hypothesis is still appropriate.

We first note that the original ‘Causal Steps Test’ specified by Judd and Kenny (1981) and Baron and Kenny (1986) has some significant limitations built into its structure. Through this definition, only three conclusions are necessary to reach mediation, first, that the treatment affects the outcome, next, each variable in the ‘causal chain’ affects the variable following it, and lastly, the treatment has no effect on outcome, after controlling for all mediating variables. However, this has the obvious limitation of providing no estimation for how much of the total effect is due to the indirect effect of X on Y, and how much is due to the direct effect of X on Y. Likewise, we cannot provide standard errors for potential confidence intervals. This causal structure has obvious difficulty in cases of parallel (multiple) mediators, as compared to serial (causal chain) mediators. Furthermore, it can’t provide a ‘joint test’ of the three conditions (treatment, mediator, outcome) in conjunction. Lastly, the causal steps test cannot detect cases of mediation wherein the indirect and direct effect are in opposite directions, effectively “canceling out” each other.

Another common method for mediational analysis, the “Difference in Coefficients” method popularized by Freedman & Schatzkin (1992); McGuigan & Langholtz (1988); and Olkin & Finn (1995) has fewer, and different weaknesses. The difference in coefficients method primarily assesses intervening variable effects by comparing the relationship between the independent and dependent variable both before and after adjusting for the proposed mediator. One obvious gain to this increased flexibility is being able to test various null hypothesis about any pair of variables. The main notable weakness is that this difference in coefficients method relates to only one specific intervening variable. This framework does not generalize between the relative coefficients and joint significance of models with multiple potential mediators.

Directly addressing this primary weakness, Imai, Keele and Yamamoto (2010) theorized a more general framework, apart from previous models derived under a linear structural equation framework. Under a specific form of a sequential ignorability assumption, they indicate that the ‘average causal mediation effect’ (ACME) can be nonparametrically identified. The sequential ignorability assumption here can be roughly defined as two ignorability assumptions made in sequence. First, given the observed pretreatment confounders, the treatment assignment is assumed to be ignorable, that is, statistically independent of potential outcomes and potential mediators. For example, this assumption would be satisfied in most clinical trials as participants are randomly assigned to treatment and control groups, but not in any studies where participants can self-select. The second assumption is that our mediator is ignorable given the observed treatment and pretreatment confounders. That is, the second part of the sequential ignorability assumption is made conditional on the observed value of the ignorable treatment and the observed pretreatment confounders. An alternative phrasing is, if our mediator is ignorable, it implies that for patients with the same treatment status and pre-treatment characteristics, the mediator can be treated as if it were randomized. Imai, Keele, and Tingley (2010) note that this second assumption is extremely strong, as there is reasonable possibility that unobserved variables can confound the relationship between the outcome and mediator even after conditioning on all observed covariates and treatment state. This is one of the primary limitations. Likewise, another imitation is that it is very difficult to know for certain whether our mediator can be held to be ignorable even after we collect as many confounders as possible Definitionally, this is a ‘nonrefutable’ statement that cannot be directly tested from the observed data. While we note that detection of theoretical confounding variables is a significant limitation, Imai and colleagues propose that ‘sensitivity analysis’ is an appropriate tool to address this weakness. Sensitivity analysis addresses these nonrefutable assumptions by painting an example of what the world would have to be like for our assumptions to be proven wrong. By quantifying how badly our assumptions of ignorability need to be violated for the original conclusion to be reversed, we can note how sensitive our inference is. With a highly sensitive inference, a slight violation of the assumption could lead to a different conclusion, and we should not trust this CMEs analysis. Conversely, if our inference is tolerant to significant violations of our ignorability assumptions, and results in the same conclusion, we can be confident in our results even in the presence of unaddressed confounders.

What are the advantages of using Bayesian methods when studying Casual Mediation Effects?

Bayesian methods can address some of the limitations of CMEs analysis, improving our ability to study causal mediational effects. For example, when we have a dichotomous mediator and dichotomous outcome, many of our parameters become difficult or impossible to identify (as they are counterfactuals that cannot exist in our data itself). One method to address this is using Bayesian estimation to determine our direct and mediated effects (Elliott & Raghunathan, 2010). Our dissassociative effect of treatment can be estimated as the intent to treat effect for subjects where our mediator is not allowed to change under our different treatment assignments, and conversely, we can see an associative effect when our mediator is allowed to change under different treatment assignments. The Bayesian approach furthermore works well because we can address the nonidentifiable parameters of our direct and mediated effects by using posterior distributions for our parameters of interest, instead of point estimates.

Another application of Bayesian methods to improve CMEs analysis occurs in the stage of sensitivity analysis. Bayesian techniques can work very well to find potential unmeasured confounders (McCandless & Somers 2017). The Bayesian methodology is unique in that it assesses for confounding in all 3 potential locations simultaneously, mediator to outcome confounding, treatment to outcome confounding, and treatment to mediator confounding. The main technique can be seen as an extension of previous work on Bayesian Sensitivity Analysis. Conceptually, the procedure works by introducing a latent binary variable, here named U, that can take values of 1 or 0, indicating the presence or absence of a theorized unmeasured confounder. In our causal diagram, the latent variable U is linked to each of our measured variables (treatment, mediator, and outcome). Uniquely, U here is simultaneously a confounder for all three potential relationships. We then seek to sample from our posterior distribution of our model parameters, by using the marginal likelihood function integrating over U. This sampling occurs using Monte Carlo sensitivity Analysis. Ideally, our sample can be then used to derive various summary statistics (median, mode, interval estimates, etc.).

One significant field of difficulty is interpretation of multiple mediator based hypothesis. Fortunately, work by Kim, Daniels, Hogan, Choirat, and Zigler (2019)*,* describes exactly that, a study in which Bayesian methods are used for a potential multiple mediator analysis on various environmental factors that affect power-plant emissions, and whether the installation of C02 ‘scrubbers’ leads to cleaner emissions. The main goal of our Bayesian methods here is to allow for a nonparametric modeling approach for our observed emissions and pollution metrics. Vitally, we must estimate our posterior distributions, as they cannot be computed directly from observed data. This is because potential outcomes cannot be jointly observed in both cases of the scrubber being installed or not; The a-priori counterfactual case is impossible to observe.

What is a scenario where CMEs could be used to address mechanisms associated with anthropogenic climate change causes of [Increased hurricane intensity]?

Hurricanes are some of the most devastating phenomena known to man, with the capability to destroy entire communities in an instant. The Intergovernmental Panel on Climate Change report in 2016 noted that hurricanes were one of the most common weather-related events driving forced migration and involuntary displacement. Notably, this occurs through the direct damage of homes and property, as well as the indirectly, through effects such as lost capability to earn wages and income. In the United States, the 2020 Hurricane season experienced an unprecedented 30 named storms, with large regions of hurricane level precipitation affecting broad swathes of the continent (Reed, Wehner, and Zarzycki, 2022). While the full extent of the damage is still unknown, losses total to at least $40 billion and counting. Considering this, being able to forecast and predict increased hurricane intensity is of obvious and potentially life-saving value, and is worth our full attention. We briefly cover contemporary research illustrating current methods in the field of Meteorology on addressing the anthropogenic climate change causes of increased hurricane activity. Then, we will introduce Causal Mediation Effects analysis as an appropriate methodology for understanding how potential mechanisms (here, anthropogenic climate change) can result in a particular causal outcome (here, increased hurricane intensity).

First, while it may seem abundantly obvious, we briefly review evidence of Anthropogenic climate change on factors that could affect hurricane formation and intensity. We first address changes in hydroclimate change. In general, while anthropogenic global warming has led to greater drying in the subtropics and midlatitudes, a significant issue with analysis is how much ‘noise’ there is in the data (Seager & Naik, 2012). This ‘noise’, in the form of natural climate variability (outside of anthropoegenic sources), can occur on interannual time scales, thus it can be difficult to attribute correctly what the causes of climate change are for any given year. A meta-analysis by Zhai, Zhou, and Chen (2018) directly reviews evidence on who or what should climate change be attributed to. The researchers find that Sea Surface Temperature has had significant anthropoegenic increase, from 1951 to 2010, with more than half of the total observed increase likely due to human causes (IPCC 2013). Furthermore, looking at a specific region of the world, there is strong evidence that between between 1948 to 2012, that 1 degree Celsius of the total 1.7 degree Celsius of sea surface temperature increase in Canada was due to human causes (Wan et al., 2018). Changes in precipitation can likewise be very complex, global scale weather dynamics in different areas of the world can ‘counteract’ each other, reducing the total magnitude of global average weather effects (Zhang, Zwiers, Hegerl, Lambert, Gillett, Solomon, Stott, and Nozawa, 2007). However, best evidence of anthropoegenic effects on precipitation indicate that human causes have contributed from 1925-1999 to roughly 70% of the observed land precipitation between 40 degrees N to 70 degrees N, 30% of the observed drying between 0 degrees to 30 degrees N, and 95% of the moistening trend between 0 degrees to 30 degrees S. In general, there is very strong evidence of anthropogenic climate change for precipitation and sea surface temperatures, two crucial precursors to likelihood of hurricane formation and hurricane intensity.

We next briefly discuss current research on what proportion of hurricane formation likelihood and intensity can be directly attributed to human climate change causes. The current best contemporary method in the meteorological sciences is what is called a ‘Hindcast’ attribution approach (Reed, Stansfield, Wehner, and Zarzycki, 2020; Reed, Stansfield, Wehner, and Zarzycki, 2021; Reed, Wehner, and Zarzycki, 2022), which has been pioneered in its application on hurricane climatology by Kevin A. Reed and his colleagues. This ‘Hindcast’, is essentially a computer simulation of what weather could have theoretically occurred, given several of the following conditions. There must be observed human-caused changes in the composition of the atmosphere, including greenhouse gases and aerosols, credible estimates of human-induced changes in the ocean surface temperatures and mean atmospheric state aloft, and evidence that cyclogenesis has occurred under a plausible synoptic environment (which is considered the most stringent criteria). This ‘Hindcast’ functions as a simulation of the ‘counterfactual’ situation (what climate we would have without anthropogenic climate change), which by definition, cannot be observed in the real-world. After generating this ‘Hindcast’, the simulation is compared against actual measured output from the hurricane itself, as well as a second simulation set including the impact of anthropogenic climate change. For example, in the case of Hurricane Florence in 2018, Reed and colleagues determined that 10% of the extreme rainfall volume, 80 km of the size of the storm could be attributed to climate change differences caused by humans. Another study conducted on Hurricane Dorian determined that human caused climate changes in air temperature, humidity, and sea surface temperatures, likely resulted in a 16% increased likelihood of daily extreme rainfall, and 7% greater total rainfall accumulation. In general, across the entire 2020 hurricane season, extreme rainfall due to human-induced climate change increased in total accumulated volume by 5%. According to Reed and colleagues, “The best direct estimate of anthropogenic individual storm impact can be seen in rainfall increases. Storm accumulated rainfall is likely limited by available moisture, which has had direct anthropogenic human impact”.

Finally, we discuss what elements and scenarios in which CMEs analysis would be appropriate for when examining anthropogenic causes of increased hurricane intensity. In general, attribution for extreme weather and climate events can have varying degrees of difficulty depending on the type of climate (Tilley, 2016, p. 33). The National Academy of Sciences concluded that there is relatively high confidence when predicting extreme temperature events (cold and heat waves) as there are less variables to account for. In comparison, there is only medium confidence when predicting extreme precipitation and drought events, as there is a great deal of variables accounting for the complex land/sea/air feedback of moisture travel in the atmosphere. Predicting truly extreme weather occurrences, such as hurricanes or other severe convective storms, is even more difficult, as the number of variables and potential interactions continues to ramp up. The main value of CMEs analysis in these cases is twofold. First, current research has seemed to focus primarily on simulating the ‘counterfactual’ world that could exist, which is unbelievably difficult to parameterize correctly and extremely computing resource intensive even when parameters can be plausibly assigned. In contrast, once some (to be fair, relatively strict) explicit and transparent assumptions are made about observable data and the *a-priori­* counterfactuals that follow, it is significantly more computationally and conceptually simple. Secondly, mediational hypothesis provide evidence about the mechanisms and circumstances behind a given outcome, which is necessary when determining how to best address the multiple causes of increased hurricane likelihood and intensity. Specifically, CMEs analysis is ideal for circumstances where the indirect effect and direct effect of a variable are in the opposite direction, and thus ‘cancel’ each other out. For example, this is the case when looking at the effect of sea surface temperature (SST) on hurricane intensity (Balaguru, Foltz, Leung, Hagos, and Judi, 2018). Generally, increased SST leads to greater likelihood of intense hurricane formation, however, as hurricane intensity increases, SST leads to increased ‘storm induced vertical mixing’. This ‘storm induced vertical mixing’ in some part leads to a dynamic reduction in SST, and thus, has both a direct effect leading to increased hurricane likelihood as well as an indirect effect that reduces hurricane likelihood. Hypothesis such as these are significantly easier to model when using a CMEs analysis framework.

References

McGuigan, K., & Langholtz, B. (1988). A note on testing mediation paths using ordinary least-squares regression. *Unpublished note*, 144-158.

IPCC, 2013: Summary for Policymakers. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Judd, C. M., & Kenny, D. A. (1981). Process analysis: Estimating Mediation in Treatment Evaluations. *Evaluation Review*, *5*(5), 602–619. https://doi.org/10.1177/0193841X8100500502

Emanuel, K. A. (1988). The Maximum Intensity of Hurricanes. *Journal of the Atmospheric Sciences*, *45*(7), 1143–1155. https://doi.org/10.1175/1520-0469(1988)045<1143:TMIOH>2.0.CO;2

Freedman, L. S., & Schatzkin, A. (1992). Sample size for studying intermediate endpoints within intervention trials or observational studies. *American Journal of Epidemiology*, *136*(9), 1148–1159. https://doi.org/10.1093/oxfordjournals.aje.a116581

Olkin, I., & Finn, J. D. (1995). Correlations Redux. *Psychological Bulletin*, *118*(1), 155–164. https://doi.org/10.1037/0033-2909.118.1.155

Zhang, X., Zwiers, F. W., Hegerl, G. C., Lambert, F. H., Gillett, N. P., Solomon, S., Stott, P. A., & Nozawa, T. (2007). Detection of human influence on twentieth-century precipitation trends. *Nature*, *448*(7152), 461–465. https://doi.org/10.1038/nature06025

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

Mcmaster, M. L., Kristinsson, S. Y., Turesson, I., Bjorkholm, M., & Landgren, O. (2010). A comparison of methods to test mediation and other intervening variable effects. *Psychol Methods*, *7*(1), 19–22.

Imai, K., Keele, L., & Tingley, D. (2010). A General Approach to Causal Mediation Analysis. *Psychological Methods*, *15*(4), 309–334. https://doi.org/10.1037/a0020761

Imai, K., Keele, L., & Yamamoto, T. (2010). Identification, inference and sensitivity analysis for causal mediation effects. *Statistical Science*, *25*(1), 51–71. https://doi.org/10.1214/10-STS321

Strobl, C. (2010). Advances in Social Science Research Using R . In *Journal of Statistical Software* (Vol. 34, Issue Book Review 2). https://doi.org/10.18637/jss.v034.b02

Elliott, M. R., Raghunathan, T. E., & Li, Y. (2010). Bayesian inference for causal mediation effects using principal stratification with dichotomous mediators and outcomes. *Biostatistics*, *11*(2), 353–372. https://doi.org/10.1093/biostatistics/kxp060

Seager, R., & Naik, N. (2012). A mechanisms-based approach to detecting recent anthropogenic hydroclimate change. *Journal of Climate*, *25*(1), 236–261. https://doi.org/10.1175/JCLI-D-11-00056.1

Canty, T., Mascioli, N. R., Smarte, M. D., & Salawitch, R. J. (2013). An empirical model of global climate-Part 1: A critical evaluation of volcanic cooling. *Atmospheric Chemistry and Physics*, *13*(8), 3997–4031. https://doi.org/10.5194/acp-13-3997-2013

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., & Imai, K. (2014). Mediation: R package for causal mediation analysis. *Journal of Statistical Software*, *59*(5), 1–38. https://doi.org/10.18637/jss.v059.i05

National Academy of Sciences, & Tilley, E. (2016). Attribution of Extreme Weather Events in the Context of Climate Change. In *Attribution of Extreme Weather Events in the Context of Climate Change*. https://doi.org/10.17226/21852

Knutson, T. R., Zhang, R., & Horowitz, L. W. (2016). Prospects for a prolonged slowdown in global warming in the early 21st century. *Nature Communications*, *7*. https://doi.org/10.1038/ncomms13676

Pieters, R. (2017). Meaningful mediation analysis: Plausible causal inference and informative communication. *Journal of Consumer Research*, *44*(3), 692–716. https://doi.org/10.1093/jcr/ucx081

Zhai, P., Zhou, B., & Chen, Y. (2018). A Review of Climate Change Attribution Studies. *Journal of Meteorological Research*, *32*(5), 671–692. https://doi.org/10.1007/s13351-018-8041-6

Balaguru, K., Foltz, G. R., Leung, L. R., Hagos, S. M., & Judi, D. R. (2018). On the use of ocean dynamic temperature for hurricane intensity forecasting. *Weather and Forecasting*, *33*(2), 411–418. https://doi.org/10.1175/waf-d-17-0143.1

Miočević, M., Gonzalez, O., Valente, M. J., & MacKinnon, D. P. (2018). A Tutorial in Bayesian Potential Outcomes Mediation Analysis. *Structural Equation Modeling*, *25*(1), 121–136. https://doi.org/10.1080/10705511.2017.1342541

Hale, S. E., & Ojeda, T. (2018). Acceptable femininity? Gay male misogyny and the policing of queer femininities. *European Journal of Women’s Studies*, *25*(3), 310–324. https://doi.org/10.1177/1350506818764762

Wan, H., Zhang, X., & Zwiers, F. (2019). Human influence on Canadian temperatures. *Climate Dynamics*, *52*(1–2), 479–494. https://doi.org/10.1007/s00382-018-4145-z

IPCC. (2019). Foreword Technical and Preface. In *Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*.

Kim, C., Daniels, M. J., Hogan, J. W., Choirat, C., & Zigler, C. M. (2019). Bayesian methods for multiple mediators: Relating principal stratification and causal mediation in the analysis of power plant emission controls. *The Annals of Applied Statistics*, *13*(3), 139–148. https://doi.org/10.1214/19-AOAS1260

McCandless, L. C., & Somers, J. M. (2019). Bayesian sensitivity analysis for unmeasured confounding in causal mediation analysis. *Statistical Methods in Medical Research*, *28*(2), 515–531. https://doi.org/10.1177/0962280217729844

Reed, K. A., Stansfield, A. M., Wehner, M. F., & Zarzycki, C. M. (2020). Forecasted attribution of the human influence on Hurricane Florence. *Science Advances*, *6*(1), 1–9. https://doi.org/10.1126/sciadv.aaw9253

Physical, T., & Basis, S. (2021). Climate Change 2021—The Physical Science Basis. In *Chemistry International* (Vol. 43, Issue 4). https://doi.org/10.1515/ci-2021-0407

Reed, K. A., Wehner, M. F., Stansfield, A. M., & Zarzycki, C. M. (2021). Anthropogenic influence on Hurricane Dorian’s extreme rainfall. *Bulletin of the American Meteorological Society*, *102*(1), S9–S15. https://doi.org/10.1175/BAMS-D-20-0160.1

Magnan, A. K., Pörtner, H. O., Duvat, V. K. E., Garschagen, M., Guinder, V. A., Zommers, Z., Hoegh-Guldberg, O., & Gattuso, J. P. (2021). Estimating the global risk of anthropogenic climate change. *Nature Climate Change*, *11*(10), 879–885. https://doi.org/10.1038/s41558-021-01156-w

Reed, K. A., Wehner, M. F., & Zarzycki, C. M. (2022). Attribution of 2020 hurricane season extreme rainfall to human-induced climate change. *Nature Communications*, *13*(1), 1–6. https://doi.org/10.1038/s41467-022-29379-1