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Task 11 –Initial Guidance and Recommendations for Climate Informed Science Design Approach

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16. Abstract		
A review of climate science reports relevant to extreme precipitation planning for their appropriateness and application to extreme precipitation design was completed for the Ohio Department of Transportation (ODOT) Office of Hydraulic Engineering. The report responds to questions posed by ODOT related to the climate science reports, encompassing a range of topics, including context around the greenhouse gas emissions scenarios used in the reports, uncertainty associated with precipitation projections at various return periods, and interpretation of results. Points of clarifications are provided, and potential analyses or reviews are proposed in select responses.		
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Chapter 1: Introduction

1.1 Scope of Work

This report provides an overview of how climate models resolve high-intensity, low-frequency precipitation as relevant to climate change resilience planning for transportation infrastructure. In particular, the report focuses on several key research questions below as prioritized by ODOT.

- How do climate models resolve projections for high-intensity, low-frequency precipitation and how do those projections incorporate empirical observations?
- How does modeling support the conclusion that increases in the intensity of rarer, more extreme precipitation will increase more than less rare and less extreme precipitation?
- How does modeling support the conclusion that projected precipitation trends are greater than observed trends, particularly for high-intensity, low-frequency precipitation events.

Finally, the report considers initial recommendations for using a risk-based framework to apply climate projections in support of resilience planning and design.

1.2 Outline of the Report

This report is organized to address the key research questions described above. Chapter 2 summarizes key messages supported by the remainder of the report. Chapter 3 provides an overview of how climate models resolve high-intensity, low-frequency precipitation events and incorporate empirical observations. Chapter 4 discusses the importance of downscaling techniques in improving the resolution of high-intensity, low-frequency precipitation events in models. Chapter 5 summarizes the state-of-knowledge pertaining to future projections of high-intensity, low-frequency precipitation events. Finally, Chapter 6 provides high-level recommendations for applying climate projections in support of resilience planning and design.

Chapter 2: Key Messages

- Global climate models (GCMs) are the primary tools used to understand past and future climate change. Output from GCMs increasingly informs climate policy and resilience planning.
- Global climate models simulate Earth's climate based on the laws of physics, fluid motion, and chemistry. GCMs are not *directly* calibrated to observations of high-intensity, low-frequency precipitation events, but the physics (e.g., convection) governing extreme precipitation in models is parameterized, or "tuned," using empirical values of atmospheric circulation and thermodynamics. Model projections of high-intensity, low-frequency precipitation, however, are *validated* using empirical measures of extreme precipitation.
- Downscaling techniques are applied to GCM output to provide a more accurate representation of high-intensity, low-frequency precipitation. Downscaling techniques are often trained using empirical datasets.
- Intensities for rarer and more extreme precipitation events are projected to increase at a faster rate than less rare and less extreme events based on downscaled GCMs. A range of studies using GCMs, as well as some recent regional studies using empirical data, supports this conclusion.
- Observed trends in higher-intensity, lower-frequency precipitation totals increase at a lower rate than some lower-intensity, higher-frequency precipitation totals in Ohio. Trends in higher return period precipitation totals are associated with a higher degree of uncertainty in both the observed record and model projections.
- Ensembles of GCMs increase the number of data points to better represent the full future distribution of higher-intensity, lower-frequency precipitation totals. Studies using GCMs show that precipitation increases are amplified for heavier precipitation totals.
- Climate projections used in national and state climate assessments show the heaviest precipitation events are likely to increase in both frequency and intensity during the 21st century. Specifically, Ohio is projected to experience increases in the number of days with and intensity of heavy precipitation, with proportionally greater increases for heavier precipitation totals during the 21st century.
- Overall, GCMs, including most downscaled GCMs, remain limited in their ability to simulate high-intensity, low-frequency precipitation events and develop comprehensive projections of their future changes. Obstacles to modeling include challenges related to simulating small space and time scales over which some extreme precipitation events occur (e.g., severe thunderstorms and tropical cyclones) and the shortness of the historical record relative to the rarity of the event.
- Uncertainty in future precipitation projections is difficult to model and constrain due to both inconsistent precipitation observations and physical constraints and limitations in models. Ultimately, verification of extreme precipitation projections in climate models is particularly challenging.

- Models continue to improve their ability to provide a more accurate representation of high-intensity, low-frequency precipitation events, although uncertainty remains. The appropriateness of using projections of high-intensity, low-frequency precipitation to support resilience planning should be considered on a project-to-project basis and risk-based analyses can provide a framework for using projections and making science-informed decisions in the face of uncertainty.

Chapter 3: Global Climate Model Validation and Calibration

Global climate models (GCMs) are complex numerical representations of the major climate system components (atmosphere, land surface, ocean, and sea ice) and their interactions. GCMs are the primary tools used to understand past and future climate change, such as from future greenhouse gas emissions, and their output is increasingly used to inform a range of climate policy decisions and resilience projects.

3.1 Climate model parameterization and calibration

GCMs are complex, numerical models used to understand how weather and climate may change in the future, particularly how greenhouse gas emissions and other drivers will affect regional and global climate. GCMs are designed to change as different mechanisms of the climate system reach historically unprecedented states, fundamentally differing from weather models based on empirical data alone. For example, weather models entirely driven by empirical data assume the historical climate remains unchanged, while forward-looking GCMs are designed to anticipate changes exceeding historical normals.

GCMs are calibrated (or "tuned") to observational data or known properties of Earth's climate, including radiative balance, temperature, clouds, wind, and sea ice (Mauritsen et al. 2012). For example, the response of extreme precipitation during thunderstorms to warming temperatures is initially modeled with some degree of uncertainty using an existing physical understanding of the response of the climate system, such as dynamic and convective responses to warmer temperatures. These model representations, known as parameterizations, are critical to accurately represent the physics of the highest-intensity precipitation events. Parameterizations are numerical representations of complex physical processes (e.g., convection leading to thunderstorms and extreme precipitation) not initially represented well in the coarse spatial resolution of GCMs.

Next, model calibration helps constrain this model uncertainty that may arise as a result of the coarse spatial resolution of GCMs or uncertain or unknown atmospheric processes and adjusts model parameters to align output with key features of the observed climate (Hourdin et al. 2017). Most GCMs have individualized model calibration approaches, focusing on a range of parameterizations. The most common includes top-of-the-atmosphere energy flux, though models also calibrate more complex parameterizations such as cloud microphysics and atmospheric circulation that impact precipitation (Hourdin et al. 2017).

How do climate models resolve projections for low-frequency, extreme precipitation?

GCMs are "tuned" to empirical data and known properties of Earth's climate, including radiative balance, temperature, atmospheric dynamics, clouds, and wind. The models use a series of physical equations that resolve precipitation if, for example, a thunderstorm is simulated through the model representation of convection. This representation, or parameterization, is tuned by observed data.

3.2 Using empirical data to calibrate and parameterize high-intensity, low-frequency precipitation in climate models

GCMs are not directly calibrated to less frequent and heavy precipitation events, but the physics (e.g., convection and microphysics) that leads to extreme precipitation is parameterized using non-precipitation empirical values. For example, models use empirical data to parameterize the radiative, dynamic, and cloud property components that affect precipitation. For the heavier precipitation events, models do not explicitly parameterize precipitation using the Clausius-Clapeyron equation, but rather parameterize convective processes during thunderstorms with observations.

How do GCM projections incorporate empirical observations?

GCMs are not directly calibrated or modeled using observed **precipitation totals**. Rather, the physical equations used to simulate extreme precipitation, such as convection during a thunderstorm or hurricane, are parameterized, or fit, to observations of **atmospheric dynamics**, **cloud properties**, and other **physical properties** that impact precipitation totals.

Changes in temperature or cloud properties also have indirect effects on precipitation rates, and models parametrize these processes using non-precipitation empirical data. Energy and water balances are parameterized, as well, which interact with many more complex processes to influence precipitation (e.g., see Figure 1 below summarizing components influencing cloud processes that are parameterized in the ECHAM[1] model). Last, the value of saturation water vapor (maximum water-holding capacity of the atmosphere) responds to temperature according to the Clausius-Clapeyron equation (Held & Soden 2006), but the conversion of water vapor into precipitation is driven by parameterized radiative and dynamic processes in GCMs such as those represented in Figure 1.

[1] ECHAM is a GCM developed by the Max Planck Institute for Meteorology. Recent versions of ECHAM were used in IPCC assessment reports. ECHAM is used as an illustrative example of cloud processes in GCMs, but it is cautioned that each GCM has different approaches to parameterizing cloud processes.

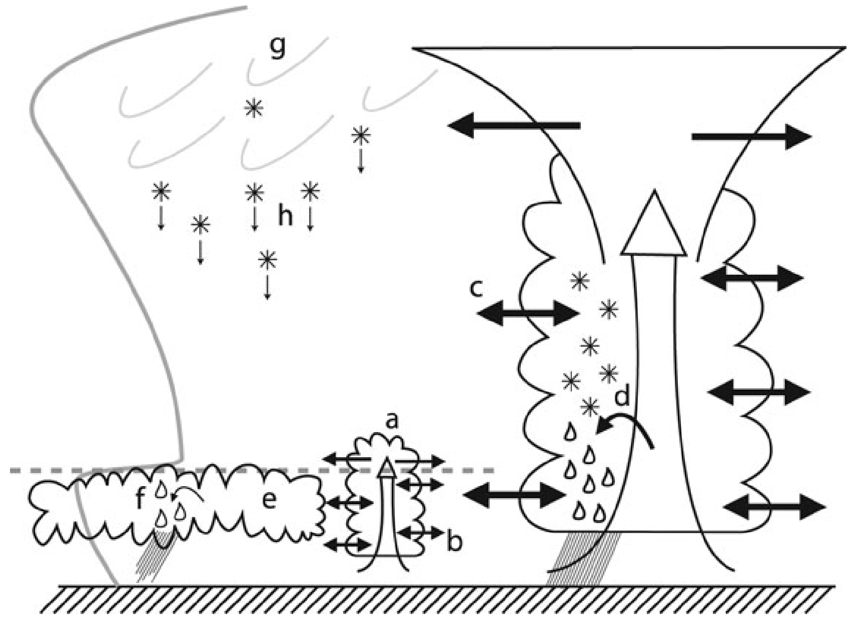

Figure 1. Illustration of the major uncertain climate-related cloud processes frequently used to tune the climate of the ECHAM model. Stratiform liquid and ice clouds, and shallow and deep convective clouds are represented. The grey curve to the left represents tropospheric temperatures and the dashed line is the top of the boundary layer. Parameters are a) convective cloud mass-flux above the level of non-buoyancy, b) shallow convective cloud lateral entrainment rate, c) deep convective cloud lateral entrainment rate, d) convective cloud water conversion rate to rain, e) liquid cloud homogeneity, f) liquid cloud water conversion rate to rain, g) ice cloud homogeneity, and h) ice particle fall velocity. Adapted from Mauritsen et al. (2012).

GCMs represent the highest-intensity extreme precipitation events at relatively coarse grid resolution using convective parameterization schemes, or physical representation of severe weather (e.g., thunderstorms) (Chan et al. 2014). Precipitation is primarily simulated in GCMs through microphysics and cumulus parameterization schemes that model large-scale and convective precipitation, respectively. Convective precipitation, precipitation that falls during high-intensity thunderstorms and tropical cyclones, often represents the most extreme precipitation totals. Convection is typically parameterized to represent physical processes in simpler numerical models, in which parameters are estimated using non-precipitation empirical values (Villalba-Pradas & Tapiador 2022).

The scientific literature is limited on the exact nature of the empirical values and assumptions used in convection schemes, but Villalba-Pradas & Tapiador (2022) provide a thorough summary of the state of the science on convective parameterization in GCMs. They indicate that non-precipitation empirical data are critical to the development of convective parameterizations but highlight the limitations of observed data gaps and the inability of modern instrumentation to adequately represent convective quantities. Despite having a significant impact on precipitation extremes, parameterization equations vary by GCM and are not publicly available, limiting our ability to validate models independently. Despite this, GCMs undergo a standardized validation process as part of the Coupled Model Intercomparison Project, in which they are required to sufficiently reproduce observed climatology and other metrics. This provides more confidence in the underlying physics and parameterizations relevant to precipitation in GCMs.

3.3 Global climate model uncertainty

Understanding the basics of model uncertainty helps contextualize how models incorporate empirical extreme precipitation data. GCM projections of future climate are constrained by uncertainties stemming from future emissions scenarios, physical representations of weather, and observational and spatial limitations. These sources of uncertainty can lead to a large inter-model spread in local, regional, and global projections of climate and extreme weather variables, particularly projections of extreme precipitation (John et al. 2022; Majhi et al. 2022). Accurately quantifying the range of future changes in precipitation intensity relative to temperature is a substantial challenge due to inconsistent precipitation observations and physical constraints in models (Allen & Ingram 2002). Despite the presence of large inter-model uncertainty in the magnitude of precipitation projections, the newest CMIP6 simulations of extreme precipitation are relatively consistent in projecting an increase in 20-year return periods of annual maximum 1-day precipitation totals, with over 90% of GCMs projecting an increase during the 21st century (John et al. 2022). **This indicates that models tend to agree on the direction of extreme precipitation trends, but uncertainty remains in the magnitude of these trends, particularly due to the spatial resolution of GCMs.** One paper demonstrates that the more coarse the model is spatially (the larger the grid size) the less intense the simulated precipitation (Chen & Knutson 2008). In effect, verification of climate model projections of high-return-period precipitation using empirical data is particularly challenging and motivates the need for higher-resolution data products.

Chapter 4: Downscaling Global Climate Models and Improved Resolution of High-Intensity, Low-Frequency Precipitation

4.1 Limitations of GCMs and motivation for downscaling

GCMs are limited in their ability to provide an accurate representation of extreme precipitation events because of the small space and time scales over which these events occur relative to the resolution of GCMs. For example, a high-intensity deluge precipitation event occurring during a thunderstorm would impact a relatively small area at a sub-daily or hourly timescale. GCMs are often run at relatively coarse spatial and temporal resolutions, often over 100+ km grids and at daily or longer time scales. At these resolutions, it is difficult to fully represent small-scale convection, even with convective parameterizations (Wehner et al. 2021; Flato et al. 2013).

As a result, GCMs tend to simulate many days with light precipitation and fewer days with heavy rainfall events, often underestimating rainfall intensities during the highest-intensity precipitation events (Sun et al. 2006; Jong et al. 2023). This can partially be attributed to the differences in coarse spatial grids in GCMs relative to observed precipitation (Wehner et al. 2009; Endo et al. 2012; Asadieh & Krakauer 2015; Jong et al. 2023).

To address these limitations, downscaling techniques are used to increase model accuracy of finer-scale processes that drive more extreme precipitation. The following section details common downscaling techniques that address the issues described above and improve how climate models provide a more accurate representation of high-intensity, low-frequency precipitation events.

4.2 Downscaling techniques improve model representation of extreme precipitation

Downscaling GCMs increases the resolution and accuracy of high-intensity, low-frequency precipitation events using two primary downscaling techniques, statistical and dynamical. **Statistical downscaling** uses relationships between a finer-scale training dataset (e.g., historical observations, or forward-looking output from the Weather Research & Forecasting Model) and larger-scale GCM output. Statistical downscaling essentially "scales" coarse spatial resolution climate projections to finer spatial resolutions using weather stations or gridded historical reanalyses.[2] **Dynamical downscaling** uses high-resolution regional physical models to simulate large-scale climate processes over finer local or regional scales. These regional models are run using boundary conditions taken from the GCM to simulate the physics of weather patterns and processes, rather than representing them statistically as in statistical downscaling. This both preserves the GCM's representation of the impacts of climate change on extreme precipitation and incorporates finer-scale processes not well-represented by GCMs (NOAA 2016). For example, the convective parameterizations described in Chapter 4 are often prescribed in these regional simulations, providing a better representation of convective storms (e.g., thunderstorms) under the influence of climate change.

Localized Constructed Analogs (LOCA) is a statistically downscaled data product and has been used in many statewide and national climate assessments. As demonstrated in Figure 2, statistical downscaling in LOCA simulates higher precipitation totals over finer spatial resolutions, more accurately depicting land features and analyzing the effects of climate change on extreme precipitation at the local level.

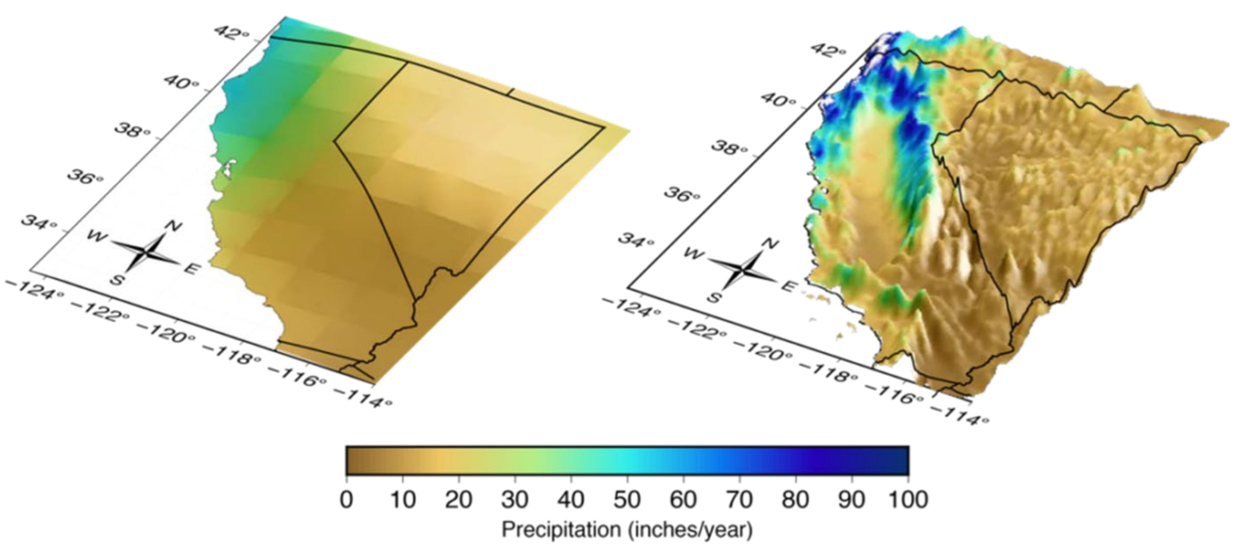

Figure 2. Two maps displaying the difference in spatial resolution of annual precipitation differences between a GCM (left) and downscaled climate data (right).[3]

Improvements have been made to statistically downscaled products in recent years to better project precipitation extremes, leading to the development of updated statistical and dynamical

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[2] Reanalyses are historical data products that assimilate observations into numerical weather prediction models to provide a spatially and temporally continuous history of weather across the Earth.

[3] Research - Downscaling at Berkeley Lab (lbl.gov)

downscaled extreme precipitation projections for use in support of the upcoming Fifth National Climate Assessment. A comparison of the original LOCA training dataset (Livneh et al. 2015) and station observations initially showed an underestimation of precipitation extremes (Pierce et al. 2021; Risser et al. 2021). The improved downscaling approach in LOCA2 uses a high-resolution gridded daily precipitation training dataset that more realistically preserves precipitation extremes by updating the time adjustment in assimilating empirical precipitation data into the model (Pierce et al. 2021). Model projections of 20-year precipitation totals average 74 and 98 mm for LOCA2 and GHCN weather stations, respectively. While the historical representation of model projections remains lower than observed values, the resulting LOCA2 dataset leads to 20-year return period daily precipitation totals that are more accurate relative to observations and 30% higher than LOCA (Pierce et al. 2021). The LOCA2 5- to 500-year return period values also better correspond to observations and increase by 20–30%, capturing tail-end precipitation extremes across North America (Pierce et al. 2023). In Ohio, 100-year events are projected to become 40-50-year events by late-21st century under a medium-emissions scenario (Pierce et al. 2023).

Downscaling is still not a perfect representation of precipitation extremes, but it is the best option available to evaluate higher-intensity, less-frequent precipitation events in the future.

The increased resolution and representation of observations of the heaviest precipitation events lead to increased user confidence in downscaled precipitation datasets to support planning decisions in a changing climate. Dynamical downscaling using physical climate models, such as the Weather Research & Forecasting Model (WRF), is the most comprehensive option to more explicitly simulate high-intensity, low-frequency precipitation, as it models processes and spatial scales most directly associated with the most extreme precipitation totals. WRF is a numerical weather model designed by the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (NOAA), the U.S. Air Force, the Naval Research Laboratory, the University of Oklahoma, and the Federal Aviation Administration (FAA). It was specifically designed for operational weather forecasting and meteorological research applications[4] and can be calibrated to observational datasets to provide a more accurate representation of extreme precipitation from convective storms, tropical cyclones, extratropical cyclones, and other significant mesoscale weather phenomena. To improve the representation of precipitation extremes in regional climates, dynamical downscaling has been applied to LOCA2 projections in California to allow convection to be dynamically produced by WRF without the use of convective parameterizations.[5] Dynamically downscaled climate models, however, are computationally expensive and, as a result, not as widely used as statistical-downscaled data products. While publicly available dynamically downscaled data exists in California, there is currently no publicly available dynamically downscaled data product in Ohio.

[4] https://www.mmm.ucar.edu/models/wrf
[5] Pierce, D. (2023). Loca version 2 (California) vs. Loca Version 2 (North America). LOCA Statistical Downscaling (Localized Constructed Analogs). https://loca.ucsd.edu/loca-version-2-california-vs-loca-version-2-north-america/

Chapter 5: Climate Model Projections of High-Intensity, Low-Frequency Precipitation

How does modeling support the conclusion that projected trends in precipitation are greater than observed trends, particularly for low-frequency, extreme precipitation amounts?

Observed trends in lowest-frequency, extreme precipitation totals increase at a slower rate than some lower-intensity heavy precipitation events in Ohio, likely a consequence rarity of the events relative to the observed timeframe. High-resolution downscaled GCMs, which are evaluated against empirical data across the United States, project that intensities for more extreme precipitation events will increase at a faster rate than less extreme events (e.g., Pierce et al. 2023; Pendergrass & Hartmann 2014). In some cases, the highest precipitation intensities are projected to increase at a rate above the Clausius Clapeyron scaling of 7% per 1˚C.

The Intergovernmental Panel on Climate Change (IPCC) states the following on projected trends in extreme precipitation, "The increase in the frequency of heavy precipitation events will be non-linear with more warming and will be higher for rarer events (*high confidence*), with a *likely* doubling and tripling in the frequency of 10-year and 50-year events, respectively, compared to the recent past at 4°C of global warming" (Seneviratne et al. 2021). This is supported by GCM projections from scientific studies that demonstrate larger relative change in return period intensities for rarer events than for less rare events (e.g., Li et al. 2021; Pendergrass 2018; Mizuta & Endo 2020; Wehner 2020), as well as the physical basis for greater increases among the highest-intensity, least-frequent events governed by the Clausius-Clapeyron equation (e.g., Wentz et al. 2007; Allan & Soden 2008; Seneviratne et al., 2021).

Observed trends in *higher-intensity, lower-frequency* precipitation totals increase at a lower rate than some *lower-intensity, higher-frequency* precipitation totals in Ohio. As highlighted in Task 1, Climate Science Review Responses to ODOT Questions, the rarest storms are infrequent relative to the observed period, and it is difficult to identify a discernable trend over such a short timeframe. While the observational record in Ohio does not capture larger increases in more-intense precipitation relative to less-intense precipitation over the recent past, GCMs and physical theory largely support this relationship across the Continental US, with evidence in the observed record in some regions around the globe (Fischer & Knutti 2016). Initially derived in physical theory alone, early GCM simulations first demonstrated the amplification of precipitation extremes as the return period increases (Fowler & Hennessy 1995). Ensembles of GCMs increase replication and the length of the timeframe to characterize the full range of the future distribution of higher-intensity, lower-frequency precipitation totals. For example, GCM ensemble projections of late-21st century precipitation under a high-emissions RCP8.5 scenario demonstrate that the probability of the higher-intensity, lower-frequency precipitation totals increases nearly exponentially with increasing precipitation totals (Neelin et al. 2017).

Using GCMs, Pendergrass (2018) demonstrates that the intensity of more extreme precipitation events increases at a faster rate than less extreme events, with the highest-intensity and lowest-frequency events outpacing the expected 7% per 1˚C warming from the Clausius-Clapeyron equation (see Figure 3). The uncertainty in climate model simulations of increasing precipitation intensity, however, also increases for the higher-intensity, lower-frequency events, as demonstrated by the increasing model spread (e.g., between top and bottom quartiles) in Figure 3, as does the likelihood of exceeding 7% per 1˚C warming in models.

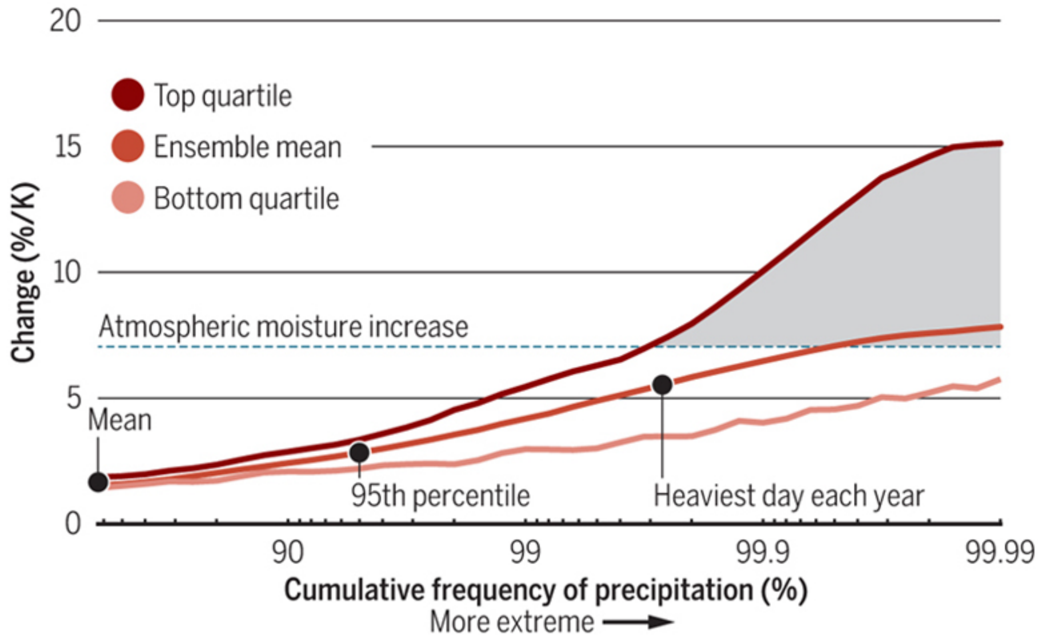

Figure 3. Projected percent change in precipitation intensity with warming temperatures. Top quartile represents the highest 25% of climate model projections, ensemble mean represents the average, and bottom quartile represents the lowest 25%. The grey area denotes changes in extreme precipitation that exceed the Clausius-Clapeyron equation. Adapted from Pendergrass (2018) and Pendergrass & Hartmann (2014).

Downscaled GCMs, trained by observed reanalysis datasets, project that intensities for more extreme, lower-frequency precipitation events will increase at a faster rate than less extreme, higher-frequency events, providing confidence in the IPCC conclusion that increases will be higher for rarer events. Downscaled GCM projections of extreme precipitation, particularly those associated with the 20-year return period from LOCA2 projections referenced in Pierce et al. (2023), align relatively well with weather station observations across the United States during the historical period (Figure 4). **Because the models represent the spatial variability in observed high-return-period precipitation well in the historical period, and demonstrate substantial improvements in representation of the observed precipitation magnitudes, users should have confidence in model representation of both empirical data and forward-looking precipitation projections.** The LOCA2 projections demonstrate that the intensities of the more extreme precipitation events could increase at a faster rate than less extreme events; all seasonal percent increases of 500-year precipitation totals outpace 5- and 50-year precipitation total increases across the United States by late century (Figure 5). **Together, these findings provide a significant link between empirical data and projected increases in higher-intensity, lower-frequency precipitation across the United States.**

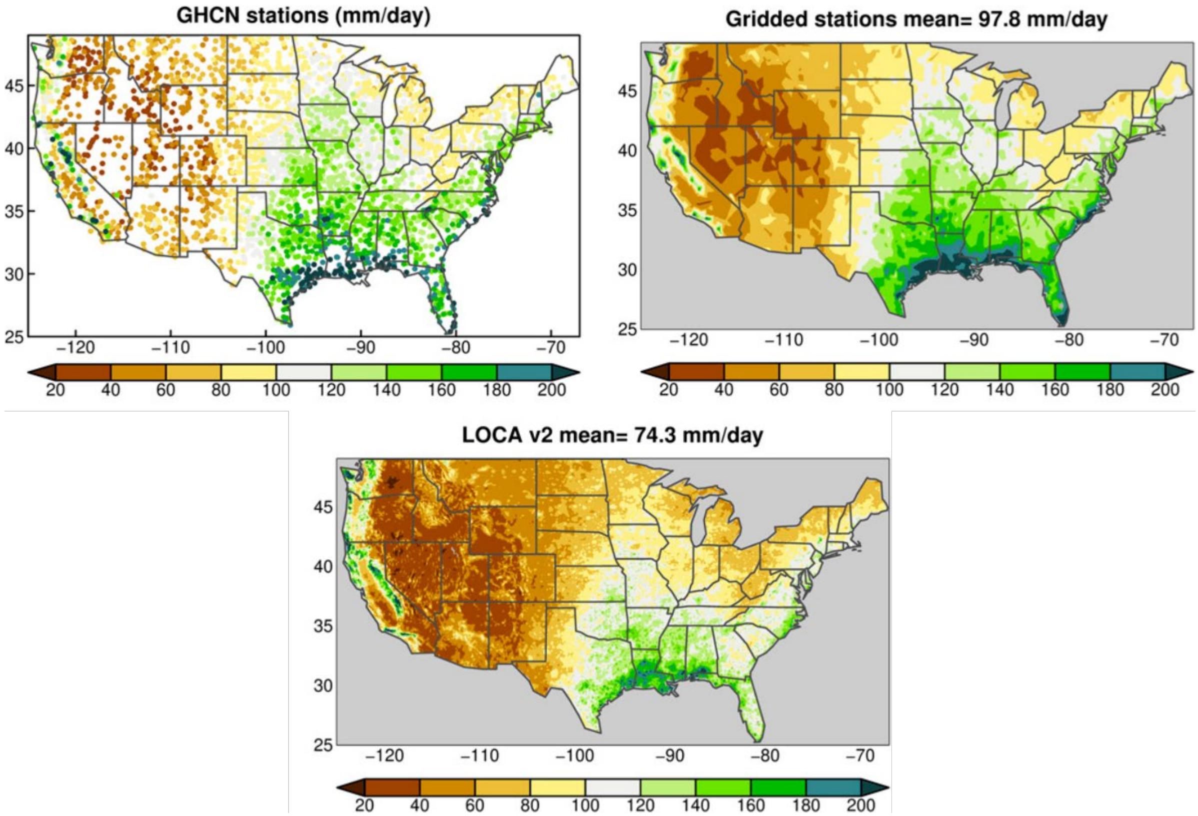

Figure 4. The 20-yr return value (mm/day) of daily precipitation over the U.S. for three datasets. (top left) 3,662 observed Global Historical Climatology Network (GHCN) weather station observations. (top right) the GHCN weather station data gridded to the LOCA grid. (bottom) Multi-model ensemble average 20-year return value from LOCA version 2 (CMIP6) during same historical period as GHCN weather station data. Adapted from Pierce et al. (2023).

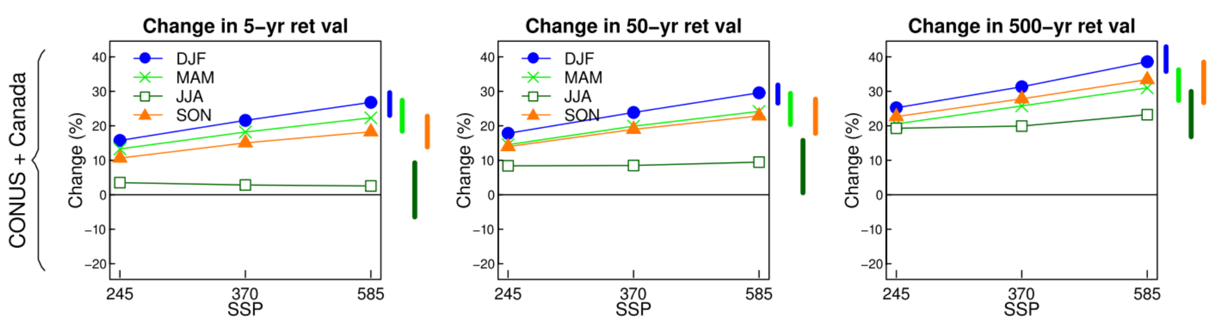

Figure 5. Multi-model ensemble average projected change (%; solid lines) in 5-, 50-, and 500-yr return values of daily precipitation as a function of Shared Socioeconomic Pathway (SSP) (x axis) averaged over Canada and the contiguous United States exclusive of Arizona and New Mexico. Different colored lines are shown for each season, as indicated by the legend. Changes are calculated from the historical period of 1950–2014 to 2075–2100. The vertical bars to the right of the panels show the interquartile ranges across the models for each season as a measure of uncertainty. Adapted from Pierce et al. (2023).

The IPCC finding that extreme precipitation increases nonlinearly with intensity primarily relies on scientific studies of return period precipitation less frequent than 100-year events(Seneviratne et al., 2021). The study by Pierce et al. (2023) described above goes further and provides projections for precipitation totals based on 500-year events, showing that heavy precipitation totals are projected to increase in frequency at a faster rate during the course of the 21st century

(Figure 6). In Ohio, 100-year events are projected to become 40-50-year events in some areas by late-21st century under a medium-emissions scenario (Pierce et al. 2023). This likely reflects the difficult requirement for much longer weather records needed to model and validate return periods longer than the observed record. The IPCC conclusion is primarily based on a physical understanding of the dynamic and thermodynamic contributions to precipitation in a convective environment (e.g., during thunderstorms) and the anticipated increase in atmospheric moisture availability that would result from projected warming temperatures (Seneviratne et al., 2021). This represents the most up-to-date state of climate science and modeling on extreme precipitation, and, while the conclusions come with a degree of uncertainty, models are the most relevant tools for planning in a changing climate.

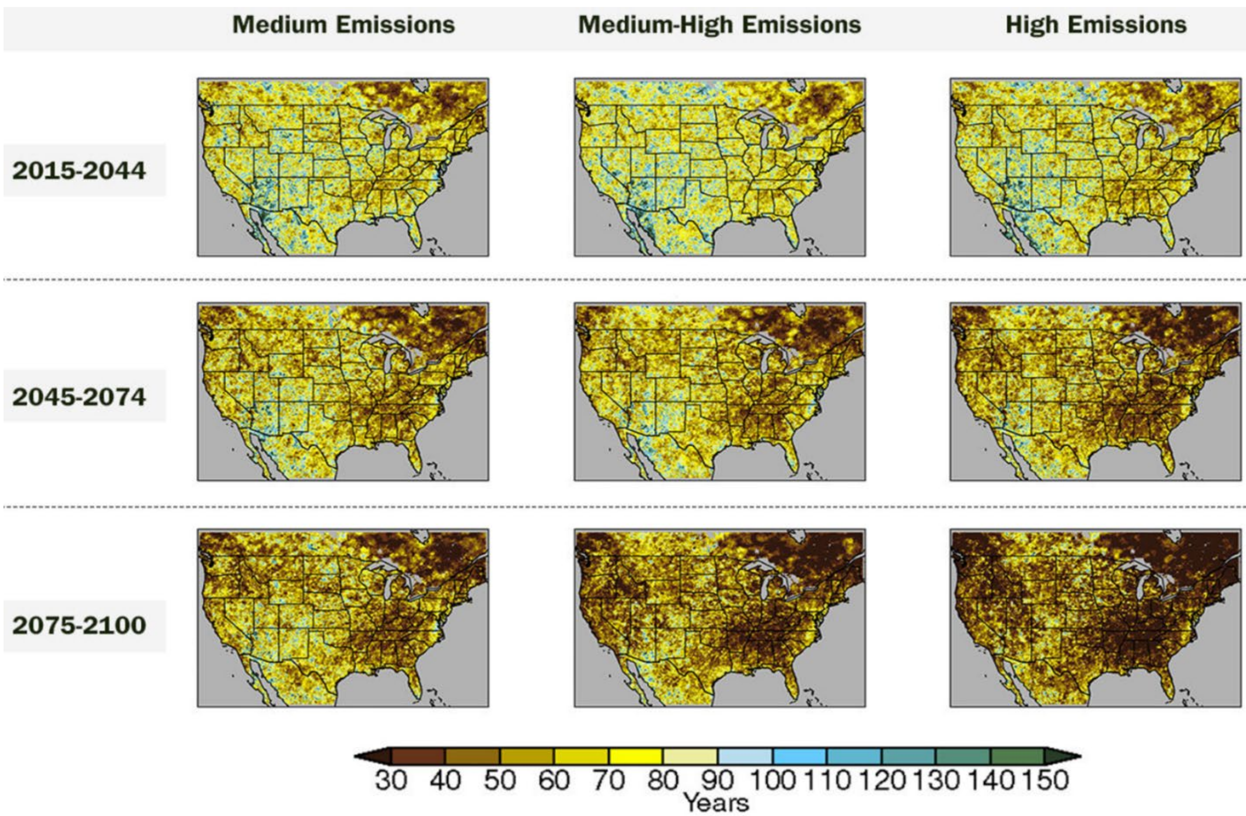

Figure 6. Future return period (in years) for the historical (1950–2014) 100-yr return value of daily precipitation. Displayed values are the median across all models that have at least one run of the indicated emissions scenarios (medium, medium-high, or high emissions). Adapted from Pierce et al. (2023).

Chapter 6: Summary of Climate Projections and Recommendations

6.1 Precipitation Projections for Ohio

The effects of global climate change on precipitation are already being experienced in Ohio. Heavy precipitation totals have historically increased in both frequency and intensity (USGCRP 2018; Bonnin et al. 2011; Ohio DOT Asset Reliability Final Report) and are projected to increase at a faster rate during the next century (e.g., Figure 6). Ohio is projected to experience increases in annual precipitation totals, primarily driven by projected increases during the winter and spring months. For heavy precipitation, projections show Ohio could experience increases in the intensity and number of days with both very heavy (historical 95th percentile precipitation total) and extremely heavy (99th percentile) precipitation, with a proportionally greater increase for extremely heavy precipitation. Projections also show that the number of days with precipitation greater than 3 inches is also projected to increase at a proportionally greater rate than days above 1 and 2 inches.[6] By the end of the 21st century, 100-year events could become 40-50-year events in Ohio under a medium-emissions scenario (Figure 6). The IPCC concluded that very rare heavy precipitation events will increase in frequency and intensity as the global temperatures warm, with changes in intensity increasing nonlinearly as the frequency of an event decreases.

As discussed in Chapters 4 and 5, high-resolution downscaled GCMs, which are evaluated against non-precipitation empirical data, improve model representation of finer-scale processes that drive more extreme precipitation. As ODOT considers the most useful results for informing potential updates to their three categories of flood-related design standards, ICF recommends that ODOT consider updating previous studies based on the most up-to-date, advanced downscaled climate models (e.g., LOCA2). While downscaling is still not a perfect representation of precipitation extremes, it is the best option available to evaluate higher-intensity, less-frequent precipitation events in the future.

6.2 Recommendations for Climate-Informed Decision Making

ICF's review of the best available science suggests that Ohio is projected to experience increases in the number of days with and intensity of heavy precipitation, with proportionally greater increases for heavier precipitation totals during the 21st century. The prospect of this change carries significant implications for hydraulic infrastructure planning and design. As ODOT considers how to incorporate this information into design and the range of risks associated with different policy options, ICF recommends two approaches to navigate the uncertainty around this decision.

Recommendation 1 – Policy Scenario Analysis. Conduct a scenario analysis to inform ODOT's understanding of the risks and costs associated with different policy options. Specifically:

(1) What if ODOT were to keep existing design practices but extreme precipitation events increase in intensity?

(2) What if ODOT were to update design practices to accommodate an increase in extreme precipitation that never materializes?

A "thought experiment" analysis to estimate high-level costs under both scenarios could be helpful in informing ODOT's overall risk tolerance around changes to design practices. For example, the first scenario has low capital costs but comes with increased risk. The latter scenario is risk-averse but comes with increased costs that would prove ineffective if resilience measures were later proven unnecessary.

The analysis could include sub-scenarios where design standards are changed to different degrees or are applied to different subsets of assets (i.e., only the most critical) similar to ODOT's current risk-based design approach. The simplest version of this analysis, for example,

[6] Projections for Ohio are from the 2020 Ohio DOT Asset Reliability Final Report.

could involve modeling the risks of action versus inaction on example assets covering the main typology of ODOT's hydraulic infrastructure and extrapolating the results statewide. Of note to ODOT, this analysis could be within the scope of ODOT's ongoing Resilience Improvement Plan project led by the Office of Statewide Planning and Research.

Recommendation 2 – Pilot Integration of Climate Model Projections into H&H Modeling. In addition to or instead of the scenario analysis above, ODOT could begin with an initial pilot to sensitivity test H&H design decisions to different climate change factors. For example, on select upcoming design projects, evaluate design options under a baseline (no climate change) scenario as well as under a scenario with changes in extreme precipitation. Practitioners would perform standard H&H modeling under each scenario to evaluate the implications for design decisions.

Overall, adaptation and resilience planning to address climate risk depends on the availability of robust extreme weather and climate data. Scientists and practitioners rely heavily on empirical data and forward-looking climate models to address this need. Observations provide a baseline understanding of climate risk for near-term planning, while climate models provide a longer-term perspective on climate risk that may well exceed the baseline historical risk. ODOT should consider trends in both observed and model-projected extreme precipitation to inform their planning decisions going forward.

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