Equipping Municipalities with Climate Change Data to Inform Stormwater Management

February 2022

Version 1.0

Final report prepared for the Minnesota Stormwater Research Council, University of Minnesota Water Resources Center

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Acknowledgements

The authors would like to thank Kenny Blumenfeld and Stefan Liess for their expert feedback and Conor Mckenzie for assistance with literature review.

This project was supported by the Minnesota Stormwater Research and Technology Transfer Program administered by the University of Minnesota Water Resources Center. Financial support was provided through an appropriation from the Clean Water Fund established by Minnesota Clean Water Land and Legacy Amendment and from the Minnesota Stormwater Research Council with financial appropriations from:

Capitol Region Watershed District
Comfort Lake-Forest Lake Watershed District
Mississippi Watershed Management Organization
Nine Mile Creek Watershed District
Ramsey-Washington Metro Watershed District
South Washington Watershed District
Valley Branch Watershed District
Upper Mississippi River Source Water Protection Project
City of Bloomington
City of Edina
City of Minnetonka
City of Woodbury
Barr Engineering
Wenck Associates

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Table of Contents

Introduction

Climate change modeling tailored to Minnesota projects warmer and wetter conditions by the end of the century.[1] However, infrastructure planning requires information on the spatial distribution, magnitude, and frequency of extreme precipitation events. Whether the additional precipitation falls in a few extreme events in already wet years, or gradual increases spread evenly between and within years has major implications for water management planning.

The de facto standard for predicting the frequency of extreme precipitation events in the United States is the National Oceanic and Atmospheric Association's (NOAA) Atlas-14. Atlas-14 uses historical precipitation records and statistical extrapolation of extreme values to estimate the frequency of precipitation events, ranging in duration from 5 minutes to 60 days, for any location in the country. For every combination of duration and location, estimates of the depth of precipitation in inches are created for nine recurrence intervals, ranging from two to 1,000 years. Recurrence intervals, also expressed as an annual exceedance probability, represent the probability a storm will exceed a given depth (e.g., an event with a 100-year recurrence interval has an annual exceedance probability of 1/100 or 1%). These estimates are provided as maps, tables, and graphical depth-duration-frequency (DDF) curves. While Atlas-14 is widely used for infrastructure planning, a known limitation is that it assumes climate stationarity, and thus does not incorporate the effects of climate change. Considering that some of the precipitation records it uses began in the 1800s, there is growing demand for estimates that reflect a changing climate.

While demand is high, NOAA's Atlas-14 has been inconsistently funded. Recent Federal infrastructure spending has earmarked funds for updating Atlas-14, but in the interim, practitioners are seeking updated estimates[2]. Although there are many global climate models quantifying trends in precipitation, using them to predict extreme events presents several unique challenges. First, analyzing climate models typically involves averaging several models into an ensemble and looking at average values over many years. While these techniques have proved useful for predicting broad trends, they also reduce the variability that is needed to identify and extrapolate extreme events. Second, validating projections benefits from minimizing differences between historical observations and modeled historical data. The long time series, pieced together from inconsistent historical records, used to create Atlas-14 is not replicated in global models. Last, the coarse resolution required to run climate models globally is unable to represent the convection found in extreme events such as thunderstorms.

Our work addresses these challenges by using dynamically downscaled climate changes projections. This overcomes the coarse resolution of global models by using the global models as an input to a weather research simulation model, which can better simulate extreme events such as thunderstorms. However, the computational effort required to dynamical downscale models limits length of time series that can be practically produced. This is especially challenging for assessing changes in the probability of rare events, which depend on long time series to capture and extrapolate rare events. Given the limited times series in our source data, our objective was to produce a proof-of-concept application of Atlas-14 methods to dynamically downscaled climate change projections rather than authoritative estimates. We sought to address the questions:

- Can NOAA values be approximated with short time series climate change projections?
- What are the challenges of applying Atlas-14 methods to climate change projections?
- What approach produces the best alignment between NOAA values and modeled historical data?
- How similar is the amount of precipitation depth in our modeled historical results to NOAA Atlas-14 across space, duration, and frequency?
- How is precipitation intensity projected to change in the future?

Objective 1: Develop methods, data, and model processes for performing Atlas-14 depth-duration-frequency calculations on climate change projections

Climate change projections

Our work builds on previously created dynamically downscaled projections[3]. That work downscaled eight CMIP-5 models that were selected for the quality of their performance in the upper Midwest. The outputs of these models were independently dynamically downscaled using the Weather Research and Forecasting model (WRF) at five arcminute (approximately 10km) resolution. Because of the high processing requirements, downscaling was limited to four 20-year scenarios; modeled historical (HIST) 1980-1989, mid-century (MID) 2040-2059, end-century moderate emissions (END4.5), and end-century high emissions (END8.5), both 2080-2099. The mid-century scenario was only modeled for moderate emissions (RCP 4.5) because at that point the scenario is not different enough from high emissions (RCP 8.5) to warrant the additional modeling. In this work, we focus on the two end-century scenarios because the greater changes are more appropriate for resiliency planning. For detailed description of modeling methods see Liess et al[1].

Depth-Duration-Frequency estimate calculations

Following the methods described in NOAA Atlas-14 Volume 8[4]. We first calculated an Annual Maximum Series (AMS) for standard Atlas-14 durations (1, 2, 3, 4, 7, 10, 20, 30, 45, and 60 days). We limited our analysis to durations of one day or above because it was outside of the scope of this project to develop new tools to process hourly data. Daily AMS values used by NOAA can be either constrained or unconstrained. Constrained indicates that a station reports the maximum value at regular intervals (e.g., every 24-hours at midnight the total resets), while unconstrained indicates the maximum value was calculated from any interval that matches the duration of interest (e.g., the 24-hour total from 9 pm to 9pm capturing an overnight storm). Because constrained data cannot capture events that happen over the time when the interval resets, they tend to underestimate short duration (e.g., less than seven days) events. NOAA applies correction factors to durations of seven days or less. Our data was summarized at a daily timestep, which is the equivalent to a constrained AMS, therefore we applied the same correction factors used by NOAA[4].

We used the Python L-moments[5] package to calculate the L-moments of each series and fit them to a Generalized Extreme Value (GEV) function to produce depth-duration-frequency (DDF) curves. We then identified the projected precipitation depth on the resulting curves that correspond with standard Atlas-14 recurrence intervals (2, 5, 10, 25, 50, and 100 years). We omitted the 200-, 500-, and 1,000-year recurrence intervals because they are less frequently used in municipal infrastructure planning, and we did not feel the length of our time series would support projections of such rare events.

To confirm that our calculations were replicating NOAA's methods accurately, we downloaded observed AMS data for the Minneapolis-St. Paul area[6] and generated DDF curves for them using our code. We compared the outputs to the values published by NOAA and found they were very similar, and remaining differences were likely due to interpolation and regionalization methods developed by NOAA to created gridded data products from station data. Because our source data were already gridded, we did not replicate these steps.

Alternative approach testing

While the calculations described above attempted to replicate NOAA's methods as closely as possible, in some cases their methods were not applicable to our data, or we believed an alternative approach could produce better agreement between our modeled historical values and NOAA's estimates. We tested four major variations:

- 17- vs. 20-year AMS length
- Ensemble vs. independent model AMS
- Spatial aggregation timing
- Short duration extrapolated using smoothing function

Testing the agreement between our outputs and NOAA faces two fundamental challenges. First, NOAA data products have elements that we cannot replicate. Foremost is their use of a longer time series; NOAA only uses stations with 30 or more years of data. The length of NOAA's time series improves its ability to capture rare events but is confounded by climate change. Additionally, their use of interpolation and regionalization to translate station data to gridded data have the potential to introduce variation that is difficult or unnecessary to match. Despite only overlapping from 1980-1997, and the unknown influence of climate change and interpolation, we attempted to match NOAA's gridded estimates as closely as possible because it is the best reference data available for precipitation intensity estimates.

The second fundamental challenge is the multi-dimensional nature of Atlas-14 estimates. Precipitation depth estimates are specific to a place, duration, and recurrence interval, meaning that for every grid cell, there are 60 values to attempt to match. Methods that improve agreement in one dimension often change others, and it is difficult to visualize and measure changes across dimensions simultaneously.

To address the second challenge, we simplified the spatial dimension by aggregating results to the county level. This resulted in dimensions of 87 spatial units, 10 durations, and six recurrence intervals, or 5,220 values total. We visualized these values in a spreadsheet and color-coded value ranges to make biases in individual dimension stand out. We also calculated the absolute value of the percent difference between our estimates and NOAA and averaged these values across all 5,220 comparison points to estimate if an approach was improving our agreement with NOAA. We calculated standard deviation to ensure that broad improvements did not come at the expense of large disagreement in specific places or other dimensions. While many other tests are possible, we used this process because it allowed us to consistently compare multiple dimensions and visualize potential biases.

17- vs. 20-year AMS length

In the process of analyzing the data we discovered a WRF modeling artifact that resulted in exaggerated precipitation values in some places beginning in the 17^{th} year of the scenarios. These values had little influence on the long-term averages but given that we would be applying methods that are designed to extrapolate from extreme values, we tested their influence using the procedures described above. We found that the 17-year series better matched NOAA estimates than the 20-year series and opted to use the reduced series for this analysis.

Ensemble vs. independent model AMS

Interpreting climate change projections is often performed using an ensemble of many models with their values averaged together. Typically, the ensemble step is performed after all other calculations (e.g., calculating differences between models). However, our application had unique features that prompted us to examine the effects of when and if to create ensemble averages. Specifically, we questioned whether it would be best to average all of the model AMS into a single 17-year AMS, or if we should treat the models as separate observations and create a ‘136-year’ (17 years x eight models) AMS. The latter has the advantage of producing a longer AMS, although because the same WRF model was used to downscale all the global models, the outputs are not completely independent. The former has the advantage of moderating the extreme values before they are input into a function that would amplify their effects. Keeping other assumptions constant, we found that treating the models independently resulted in an average error of 13.9%, compared to 21.8% when averaging the AMS values first. Treating the models as separate observations also has the advantage of being able to approximate a long time series needed to create DDF curves, but to represent a short enough period that it is possible to assume climate stationarity.

Spatial aggregation timing

Like ensemble models, it is generally best practice to wait until after calculations are complete to perform spatial aggregation. However, given the short length of our AMS we explored using spatial aggregation to the county level as a means of increasing the amount of data provided to the GEV function. While the overall agreement was better when performing spatial averaging last, we observed that that method systematically underestimated 1-day and other short duration events when compared to estimates based on county AMS averages.

Short duration extrapolated using smoothing function

Given the systematic nature of the underestimate in our outputs, we investigated if extrapolating the short duration values based on a cubic spline function fit to the more accurate longer duration values would improve the overall agreement with NOAA values. We selected a cubic spline because NOAA applies the same function to its estimates for the purpose of creating smooth curves from independently estimated durations[4]. We replicated this step, but instead of basing it on the values for all durations, we tested basing it on all except for the first one to four durations. We found that extrapolating short duration events improved the overall agreement with NOAA in our tests. After testing several variations of extrapolation (detailed in the discussion), we chose to use values extrapolated from the cubic spline function for 1-, 2-, and 3-day duration events in this analysis.

Results and Discussion

The full set of outputs from this work comprises hundreds of maps and reports summarizing the results for every county in Minnesota. To summarize the results for this report, we focus on two simplifications. In Table 1 we aggregate the data into eight regions of the state so that all durations and recurrence intervals can be visualized for the entire state. Supplementary county reports and gridded projections provide greater detail and are more appropriate for local studies. Figures 1-4 visualize a small subset of duration-recurrence interval combinations at the resolution of the underlying data. We omit end century moderate emissions scenario (RCP 4.5) results from this report and county reports because the changes to duration, frequency, and spatial distribution are similar to the high emissions scenario, but slightly lower in magnitude. Supplementary gridded data and grid-level comparisons to NOAA data are available for all duration-recurrence interval combinations for the modeled historic and end century moderate and high emissions scenarios.

Table 1. Percent difference between NOAA and our modeled historic values for all duration-recurrence interval combinations aggregated to eight regions of Minnesota. Regional aggregation for illustrative purposes in report, generally county or grid level data is a more appropriate scale of analysis. Individual columns represent durations, groups of columns represent recurrence intervals. Cell values are the percent difference rounded to whole numbers. These values represent the error of modeled historic estimates when compared to NOAA. Rare events (50- and 100-year recurrence intervals had the most error, potentially because our limited time series did not contain enough rare events. Although our time series should have been able to represent 2-year recurrence interval events, we tended to underestimate them. Performance for 5-, 10-, and 25-year recurrence intervals was the best. Differences between -15% and 15% are shaded white, 15% to 30% light blue, 30% to 60% blue, and >60% dark blue. The shading intervals are reversed using shades of orange for negative values.

	2 year										5 year										10 year									
	1	2	3	4	7	10	20	30	45	60	1	2	3	4	7	10	20	30	45	60	1	2	3	4	7	10	20	30	45	60
Northwest	-7	-12	-13	-13	-13	-13	-11	-11	-10	-8	4	-1	-2	-2	-1	0	-1	-2	-2	-1	9	4	4	4	7	8	5	3	2	2
North Central	-7	-10	-11	-11	-11	-11	-11	-11	-11	-9	3	-1	-1	-1	1	1	-1	-2	-3	-2	8	3	4	5	7	8	5	2	0	0
Northeast	-6	-11	-12	-12	-11	-10	-11	-12	-12	-10	2	-2	-3	-3	-1	0	-2	-4	-6	-4	5	1	1	2	5	6	3	0	-3	-1
West Central	-19	-22	-23	-23	-22	-21	-19	-17	-15	-13	-13	-15	-15	-15	-13	-12	-9	-8	-8	-7	-10	-12	-12	-11	-8	-6	-3	-3	-4	-4
Metro	-10	-14	-15	-16	-14	-13	-12	-12	-11	-10	-2	-4	-4	-4	-3	-3	-2	-2	-3	-3	1	1	1	2	3	4	4	3	2	2
Southwest	-25	-27	-27	-27	-25	-23	-20	-19	-17	-14	-15	-17	-17	-16	-14	-12	-10	-10	-9	-8	-9	-11	-10	-9	-6	-5	-4	-4	-4	-3
South Central	-14	-17	-18	-18	-16	-14	-13	-13	-12	-10	-2	-5	-4	-4	-2	0	0	-1	-1	-1	4	3	4	5	8	9	8	7	6	5
Southeast	-4	-8	-10	-11	-11	-11	-10	-10	-10	-8	7	5	4	4	3	3	2	1	1	2	13	13	13	13	13	12	11	9	8	8

	25 year										50 year										100 year									
	1	2	3	4	7	10	20	30	45	60	1	2	3	4	7	10	20	30	45	60	1	2	3	4	7	10	20	30	45	60
Northwest	14	10	10	12	17	18	12	9	7	6	21	16	16	18	24	26	17	13	11	9	31	24	24	25	32	35	21	18	15	11
North Central	14	9	9	11	15	16	10	7	4	3	24	16	14	15	20	22	13	10	7	5	37	24	21	20	24	28	16	13	9	6
Northeast	10	6	6	7	10	12	7	3	0	1	16	11	10	10	14	16	9	5	2	3	24	17	15	14	17	19	11	7	4	5
West Central	-4	-7	-7	-6	-2	1	4	3	1	-1	3	-2	-3	-3	2	6	9	7	4	2	12	4	1	1	6	12	14	12	8	4
Metro	6	6	8	9	10	12	11	10	8	7	11	11	12	13	15	17	16	14	12	11	17	16	17	18	21	23	22	18	16	14
Southwest	0	-2	-1	1	4	5	4	3	3	2	7	6	7	9	12	13	11	8	8	6	15	14	16	18	21	21	18	15	14	11
South Central	12	12	14	16	20	21	20	17	15	12	18	20	22	25	29	30	29	25	22	18	26	28	31	34	39	39	38	33	29	25
Southeast	18	21	23	24	25	25	22	18	17	16	20	26	30	33	35	35	32	26	24	22	22	31	38	42	47	45	41	34	31	29

Table 2. Percent difference between our modeled historic and end century high emissions scenarios for all duration-recurrence interval combinations aggregated to eight regions of Minnesota. The largest increases were observed in northern Minnesota, especially the northwest and Red River Valley. Projections for 5- and 10-year recurrence intervals, which had the best agreement between NOAA values and our modeled historic data, show a more uniform approximately 20% increase, except for southern Minnesota. Comparisons between modeled historic data and a future scenario is the preferred way to interpret results, however, note that large overestimates in southern Minnesota in the modeled historic data can mask the magnitude of values in the end century scenario when comparing relative differences. Users should consider NOAA values, modeled historic data, and end century projections together and use assumptions appropriate for their use case.

	2 year										5 year										10 year									
	1	2	3	4	7	10	20	30	45	60	1	2	3	4	7	10	20	30	45	60	1	2	3	4	7	10	20	30	45	60
Northwest	17	16	15	15	13	13	12	11	11	11	24	23	22	21	20	19	20	20	20	21	31	30	29	28	27	27	29	30	30	31
North Central	16	15	14	13	11	10	8	8	8	8	22	20	19	18	17	16	16	16	17	18	28	27	25	24	23	23	24	25	27	29
Northeast	19	17	16	15	13	12	11	12	12	12	24	22	20	19	18	17	18	20	21	21	26	25	24	23	22	21	25	27	30	30
West Central	15	15	16	16	16	17	17	16	15	15	17	16	16	16	15	15	17	17	18	19	18	17	16	15	13	13	15	17	19	21
Metro	19	19	19	19	20	21	22	21	20	20	20	19	19	20	20	21	23	24	24	24	19	18	18	18	18	19	23	24	25	26
Southwest	5	7	9	10	13	15	16	15	15	15	3	5	7	8	11	13	16	16	17	19	2	3	4	5	7	9	14	15	17	21
South Central	8	9	10	11	13	14	15	15	15	16	5	6	7	8	10	12	15	15	16	18	4	4	4	4	5	7	12	13	14	17
Southeast	0	1	2	2	4	6	10	11	11	11	-2	-2	-1	-1	1	3	8	10	11	11	-4	-4	-4	-4	-2	-1	5	8	8	10

	25 year										50 year										100 year									
	1	2	3	4	7	10	20	30	45	60	1	2	3	4	7	10	20	30	45	60	1	2	3	4	7	10	20	30	45	60
Northwest	44	42	41	40	38	38	44	46	46	49	54	53	52	52	49	48	59	60	61	65	63	64	65	65	62	61	78	77	79	84
North Central	33	34	34	34	34	33	38	39	43	47	27	35	40	43	44	42	51	52	58	63	19	35	46	53	57	53	67	68	75	82
Northeast	21	25	27	28	28	28	35	40	43	44	14	23	29	33	35	33	46	51	55	57	5	21	31	38	42	40	58	64	69	72
West Central	15	15	14	13	10	9	12	16	20	24	12	12	12	11	8	6	10	14	20	25	7	9	9	9	5	2	7	12	20	26
Metro	18	16	15	14	14	16	21	23	26	27	19	15	13	11	11	13	20	22	26	27	19	14	10	8	7	9	17	21	25	27
Southwest	-3	-2	-1	-1	1	3	10	13	15	21	-7	-6	-6	-5	-4	-2	5	10	14	21	-11	-11	-10	-10	-9	-8	1	8	11	21
South Central	3	0	-2	-2	-2	0	6	9	11	15	1	-3	-6	-8	-8	-6	1	5	8	12	-1	-7	-11	-13	-14	-12	-4	1	4	9
Southeast	-5	-7	-8	-9	-8	-7	-1	3	4	6	-6	-10	-11	-12	-13	-12	-6	-1	1	2	-5	-12	-15	-16	-18	-17	-11	-5	-3	-1

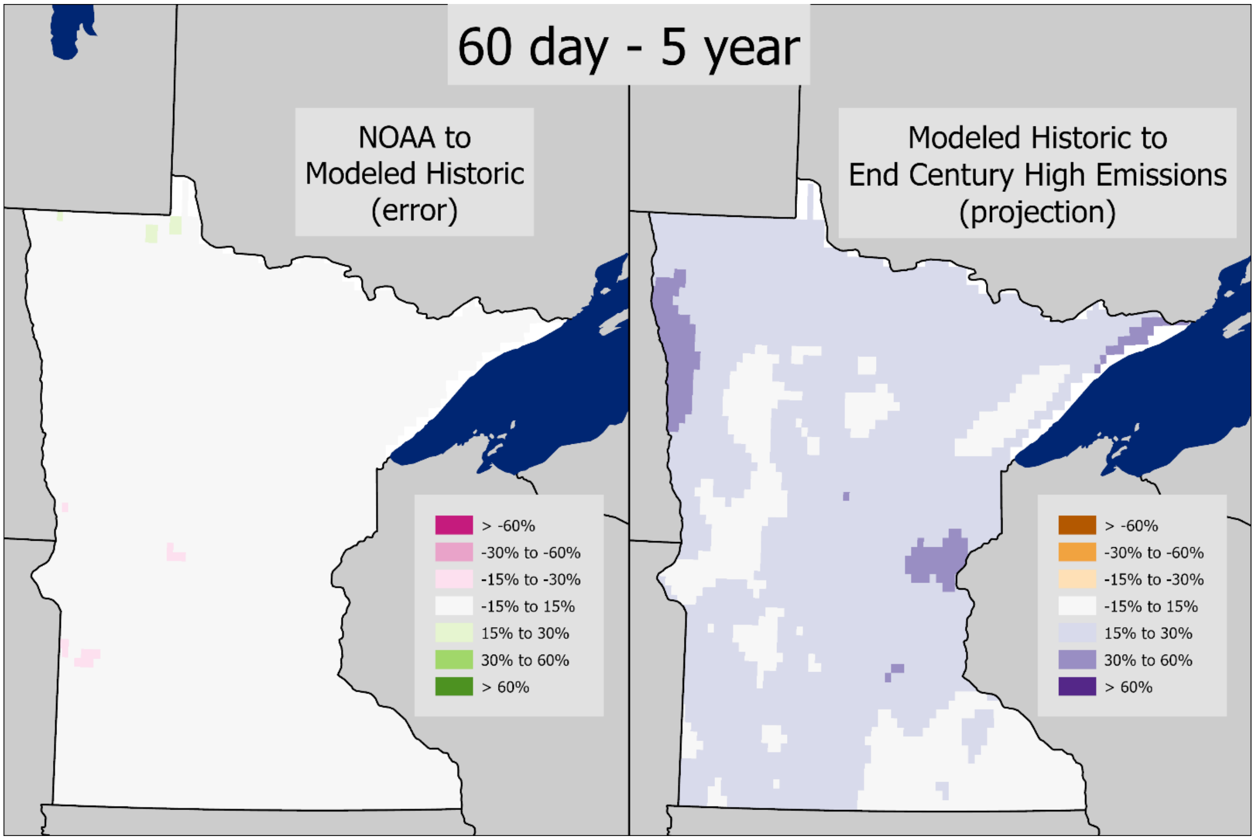

Figure 1. Maps comparing 60-day duration, 5-year recurrence interval estimates from NOAA to the modeled historic scenario (left) and comparing the modeled historic scenario to end century high emissions scenario (right). This duration-recurrence interval combination had the lowest error (5%) when averaged across all Minnesota counties. Our 60-day duration estimates matched NOAA values better than other durations across all recurrence intervals. A possible explanation for this is that climate models are better suited to estimating long term trends rather than episodic events. Because the error was minimal and uniform across the state, it is possible to interpret the projection on the right as an approximation of change from NOAA values. This projection indicates that the amount of precipitation over a 60-day period with a 20% probability of occurring will be 15-30% higher at the end of the century with high emissions. Depending on the location and recurrence interval, a 15% increase is often enough to go up one recurrence interval (i.e., a 100-year event happens twice as often, becoming a 50-year event).

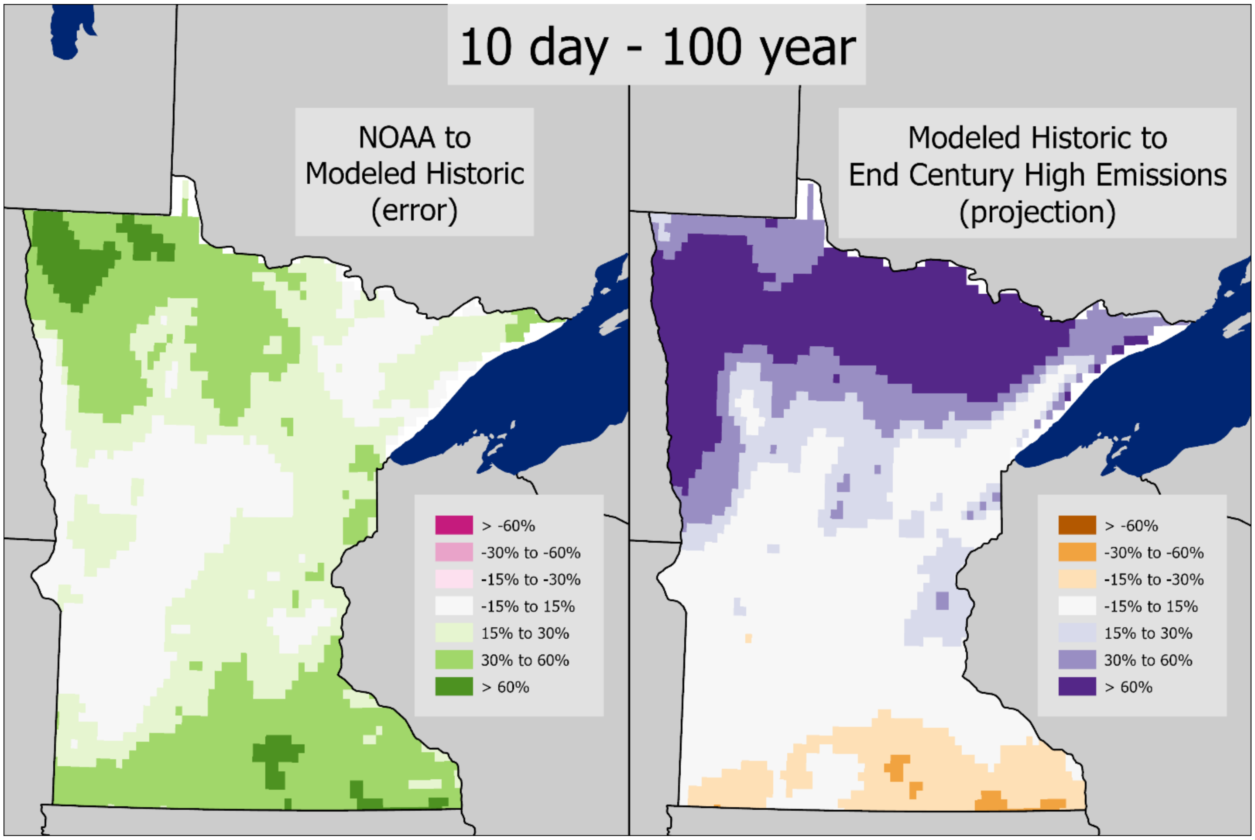

Figure 2. Maps comparing 10-day duration, 100-year recurrence interval estimates from NOAA to the modeled historic scenario (left) and comparing the modeled historic scenario to end century high emissions scenario (right). This duration-recurrence interval combination had the highest error (30%) when averaged across all Minnesota counties. Our 100-year recurrence intervals had the highest error when compared to NOAA, potentially because of our short time series used to create the estimates, or because our reference period included more climate change than NOAA's record. Apparent decreases in southern Minnesota values should be considered in conjunction with the larger overestimate of historic values in the same area.

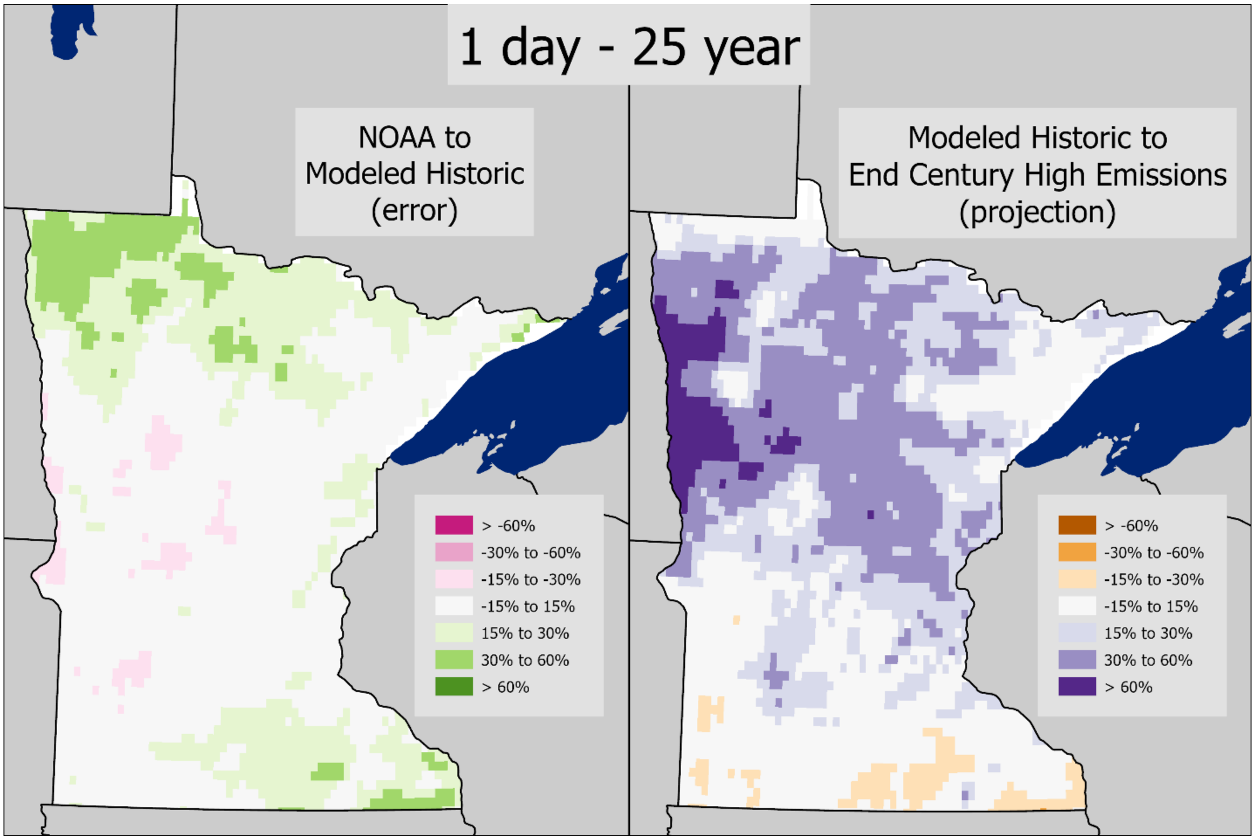

Figure 3. Maps comparing 1-day duration, 25-year recurrence interval estimates from NOAA to the modeled historic scenario (left) and comparing the modeled historic scenario to end century high emissions scenario (right). 1-day duration events are of particular interest to stormwater planners, but it was difficult to reproduce NOAA's 1-day duration values using our modeled historic data. The 1-day duration values shown here are extrapolated from a spline function fit to the 4- through 60-day duration values. This drastically improved the agreement with NOAA values for 2- through 25-year recurrence intervals but made 50- and 100-year recurrence interval estimates less accurate.

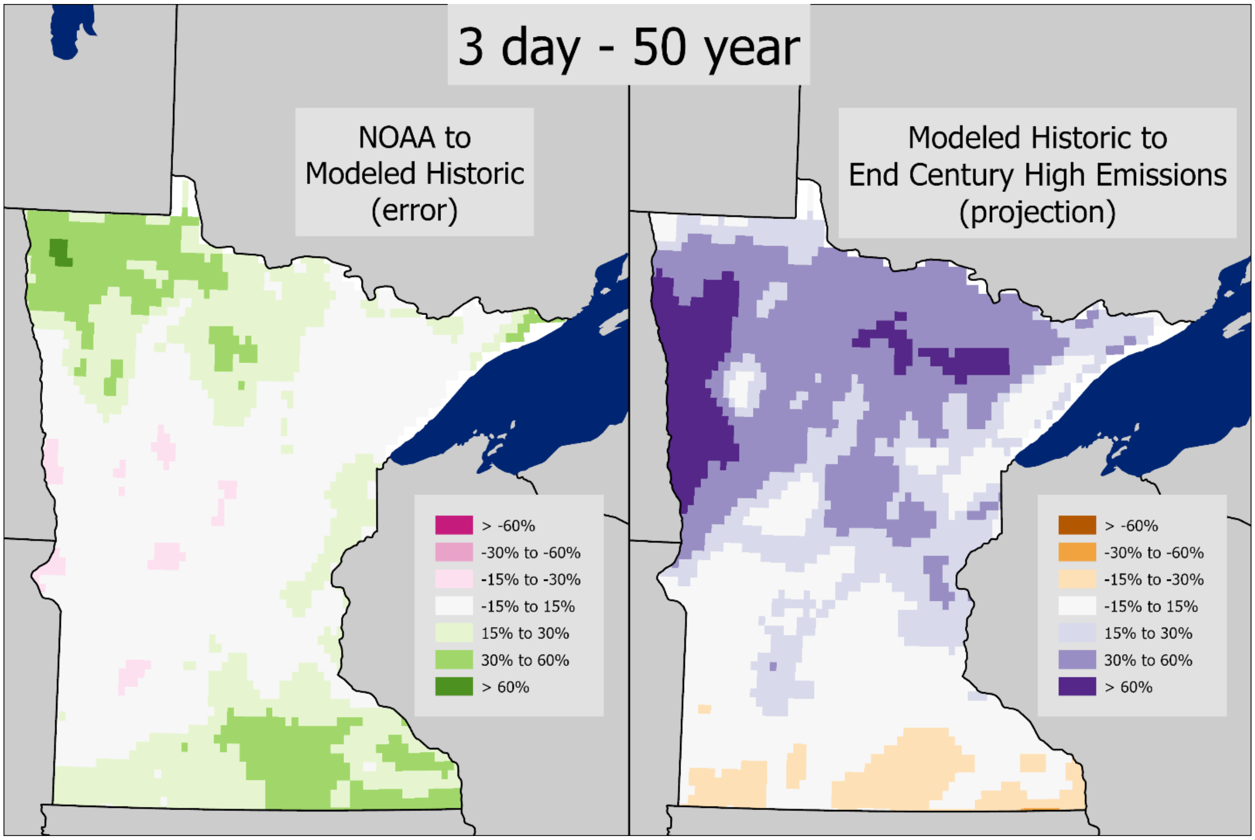

Figure 4. Maps comparing 3-day duration, 50-year recurrence interval estimates from NOAA to the modeled historic scenario (left) and comparing the modeled historic scenario to end century high emissions scenario (right). Similar to other maps, the projected decrease in southern Minnesota is paired with large errors in the reference period. The Red River Valley was a hotspot for high precipitation values both in the reference period and end century. Further modeling is needed to investigate the origin of extreme precipitation values in that region.

Suitability of these data for precipitation intensity and frequency projections

Our work tested if dynamically downscaled climate change projections 20-years or less in length could be used to estimate precipitation depth, duration, and frequency using similar methods as NOAA's Atlas-14. While the daily timestep and high-resolution nature of our data are similar to the inputs used in Atlas-14, there are few examples of this approach in the literature. We found that it was possible to replicate NOAA values using our modeled historical data that overlaps with NOAA inputs by only 17-years, from 1980 to 1997. Although the length of our time series was shorter than NOAA's criteria for inclusion, we were able to reduce the impact of this limitation by treating the eight models as separate time series. This increased the effective length of our time series from 17 to 136 years and resulted in the biggest improvement in agreement between our estimates and NOAA values of the approaches we tried.

Challenges in replicating NOAA estimates

Despite good overall agreement, there are remaining challenges in interpreting these data. Treating the eight models as separate time series improved our ability to match the shape and magnitude of Atlas-14 curves, however, that approach does not account for the influence of using the same model to downscale the inputs. We used bias-adjusted outputs of WRF and eliminated three years of each series when we discovered an artifact of the WRF modeling process in those years, but it is possible unexamined biases remain, especially in future projections where there are no validation data available.

Of particular interest are some extreme precipitation values in the Red River Valley that appear in some of the underlying models, in both the moderate and high emissions end of century scenarios. Their influence is moderated when using ensemble averages of climate projections. However, this project required maintaining variability throughout our calculations, which reduces the moderating effect of using a model ensemble. Updated global climate models and refined downscaling techniques are needed to assess if these extreme values continue to appear in climate projections.

Our values tended to underestimate precipitation depths for 2-year recurrence intervals, and overestimate depths for 50- and 100-year recurrence intervals. Alternative approaches tended to trade-off between errors at either ends of these tails, potentially because the variability in our data was less that of the observational record. An alternative explanation is that climate change influenced our 1980-1997 reference period more than the entirety of NOAA's observational record, resulting in an apparent inaccuracy in some of our values.

Extrapolating short duration values

Our methods also struggled to match NOAA's short duration event estimates. For most recurrence intervals, our 1-day duration estimates were approximately 30% lower than NOAA's. Further research is needed to understand if this phenomenon is the result of using WRF for downscaling or from the short length of our AMS data. Given the importance of 1-day and other short duration events to planners, we developed an approach that adapted NOAA's smoothing step as means of extrapolating short duration values from the more accurate long duration values. This approach improved overall agreement by 1%, but more importantly, drastically improved 1-day duration estimates.

We examined several variations of extrapolating short durations to understand the influence of the technique and to select the best fit. Extrapolating only the 1-day duration values decreased the overall error from 13.9% to 13.2%. Extrapolating 1- and 2-day durations decreased the overall error the most, to 12.7%, however, it increased the standard deviation due to large errors in a subset of counties. Extrapolating 1-, 2-, and 3-day events produced similar error, 12.9%, with lower standard deviation, and without errors concentrated in some counties. Extrapolating 1-, 2-, 3-, and 4-day duration events increased the overall error and produced warnings of poorly fitting spline functions. The drawback of this approach is that it increased the error for short duration, long recurrence interval (50 and 100 years) events. Our systematic underestimate of short duration events was ameliorated by an overall overestimate of precipitation values for 50- and 100-year recurrence intervals; extrapolating those values with longer duration estimates increased their error.

Interpretation and use suggestions

The tools developed in this analysis can be applied to future iterations of dynamic downscaling to provided needed perspective on the reliability of our projections. In the interim, users should interpret the modeled precipitation depth values with caution. In general, analysis looking at the relative difference between modeled historical data and future scenarios is the most reliable way to interpret these projections. However, in many instances, small or negative changes between the modeled historical data and the end of century projections coincide with overestimates in the modeled historical data. Users should consider NOAA values, our modeled historical data, and our end of century projections together. While users must interpret our values using assumptions appropriate for their use case, this analysis demonstrates that it is possible to approximate the shape and magnitude of Atlas-14 curves using a short time series of dynamically downscaled climate change projections.

Implications for green infrastructure

While traditional ‘gray’ infrastructure (i.e., storm sewers, gutters, and other forms of concrete water conveyance or storage systems) will always be needed to manage stormwater in dense urban environments, alternative systems such as bioswales, retention ponds, and natural vegetation may be useful for supplementing these systems as precipitation events become larger and more frequent. These interventions are particularly valuable in cities with combined storm and sanitary sewer, as green infrastructure can reduce the likelihood of sewage overflows. In cities with municipal separate storm sewer systems, green infrastructure can provide the only treatment for stormwater before it reaches surface water[7]. The primary obstacles green infrastructure faces are the costs and the much greater area required to provide the same level of management as gray infrastructure. Despite these challenges, some programs such as Portland’s downspout disconnection program had an excellent return on investment compared to gray infrastructure[8], and the space requirement is less burdensome when multiple benefits such as urban green space and air quality improvements are considered[9].

Small scale green infrastructure such as permeable pavement, rain barrels, and cisterns enable the capture and re-use of rainfall on-site. This reduces the volume of water sent to storm water systems, and can provide aesthetic value in an urban environment[10]. Tools such as bioswales, infiltration trenches, and rain gardens provide infiltration and filtration benefits, but are challenged by variable flow regimes and must be resilient to contaminants in urban environments such as road salt[9]. Urban trees can increase the efficiency of green infrastructure technologies through enhance infiltration and transpiration[11,12]. However, others have noted that careful design and management of urban landscapes is important because trees can be a source of nutrient pollution to the surface water[13].

Large scale green infrastructure typically consists of wetland complexes or large networks of other green infrastructure tools that provide filtration and storage capacity. However, their size and spatial configuration requirements make them difficult to implement in moderately dense urban environments[8]. While difficult to implement at a large scale, networks of strategically citied green infrastructure have the potential to provide multiple benefits. Researchers modeled tradeoffs between citing green infrastructure for stormwater management and five other benefits such as habitat connectivity and air quality in Detroit, Michigan[10]. They found that although green infrastructure improves habitat quantity, there was a negative relationship between performance for stormwater management and habitat connectivity, indicating that the ideal locations for stormwater management were not aligned with ideal locations for improving wildlife habitat. Conversely, they found a positive relationship between stormwater management and improvements in urban heat island and air quality. This study suggested that when multiple benefits are considered, supplemental green infrastructure for stormwater management can be comparable to gray infrastructure in terms of performance and cost[10].

Objective 1: Produce and disseminate precipitation intensity data products customized to Minnesota communities

The motive for developing the tools to apply NOAA's Atlas-14 methods to climate change projections, was to create updated precipitation frequency and intensity metrics for communities in Minnesota. However, the data's complexity makes it difficult for non-specialists to interpret. To reach as broad an audience as possible, we created two data products: county-level reports, and gridded data at the highest resolution of our underlying climate change projections.

County-level reports

We created a two-page report summarizing our main depth-duration-frequency data products for every county in the state. To summarize future projections, the report includes a graphical depth-duration-frequency curves and a table comparing our values derived from modeled historical climate conditions to values derived from modeled end century high emissions climate conditions. To summarize the ability or our data and methods to replicate NOAA's values, we include a color-coded table that summarized the differences between our values derived from modeled historical climate conditions and NOAA's values. Taken together, end-users without specialized software or expertise can both assess the capabilities of our methods and visualize the outputs for their county.

Our initial proposal called for the creation of graphical reports specific to every community with a Municipal Separate Storm Sewer System (MS4). However, after reviewing the size and distribution of MS4 communities, we opted to generate these reports for every county in the state instead. Switching to county-level averages as opposed to municipal-level boundaries has two major advantages; first, averaging over multiple grid cells produces a value more representative of the area of concern rather than a single grid cell that falls within the municipal boundaries. This is especially relevant given how upstream precipitation outside of municipal boundaries still has the potential to impact the municipality. Second, municipalities are often clustered in dense urban areas. Creating reports for municipal boundaries would over represent urban areas of the state and not provide spatially relevant data products for rural areas.

Grid-level data (maps)

Advanced users such as stormwater engineers, planners, or researchers, might want to explore data more specific to their decision context. To serve this audience, we produced our results at the highest resolution possible, approximately 10km, which is the same as the climate change projection resolution. This approach gives total control to the end-user to aggregate and analyze the data however they wish, but because the results are stored as 540 separate maps, they are more difficult to analyze. Despite the challenge, for end-users interested in a subset of duration-frequency combinations, these maps provide they best way to analyze the data because it can be aggregated to a municipality, sub-watershed, or any other spatial unit. Combined with the county-level reports, these data products offer both accessibility and flexibility for a broad range of audiences.

Data product distribution

Links to all data products are available on the project homepage:
https://z.umn.edu/atlas-14-update

The final report describing our methods and summary conclusions is available at:
https://z.umn.edu/atlas-14-update-final-report

County-level reports (.pdf files) can be downloaded at:
https://z.umn.edu/atlas-14-update-county-reports

Grid-level data (.tif maps) for all duration-frequency combinations are available at:
https://z.umn.edu/atlas-14-update-gridded-data

Objective 2: Community engagement

Plans for engagement with pilot communities were hindered by the covid-19 pandemic. In person meetings were not possible and municipal staff had limited capacity to engage on new projects. Despite this, some of our virtual engagement efforts with communities and other stakeholders are described below. These engagements informed the design of our final data products and established relationships with communities and other networks to help distribute our findings.

Early in the project we had several meetings with a consultant tasked with updating master planning documents for the cities of Staples and Hackensack. While the timeline of their planning process meant that we would not have Atlas-14 style depth-duration-frequency curves available for this planning cycle, we were able to produce changes in monthly precipitation averages from our climate change projections.

Collaborators at The Nature Conservancy (TNC) met with The Environmental Coordinator and the Stormwater Coordinator for the City of Elk River in November 2020. They discussed climate resiliency and shared climate change projections from this project. While there was interest in this work and collaboration generally, a suitable project was not identified. They will be notified of the finished products. TNC collaborators also reached out to the cities of Little Falls and Grand Rapids but did not receive a response.

Also in November 2020, TNC collaborators met with City of Alexandria staff and city engineers from Widseth. They discussed nature-based solution for increasing resilience to climate change and shared climate change projections from this project. Beginning in early 2021, TNC collaborators worked to identify a project that will improve community resiliency to climate change. They identified a nature trail that would protect and enhance a series of wetlands in the eastern sub-watershed of Alexandria, a natural area at high risk of being developed. This proactive stormwater management project will focus on finding ways to expand protection in this area, with approaches including expanded easements and restoration of degraded habitat. These nature-based solutions provide multiple benefits to nature and the community, including clean water, clean air, flood, fire, and drought risk reduction.

To advance this work, TNC collaborators presented to and engaged with several stakeholder groups, including to the City Council, Storm Water Management Committee, Park Board, Alexandria Public School staff, Kiwanis, and the Viking Sportsmen. On January 22nd, 2022, the Alexandria City Council passed a motion to direct staff to partner with TNC to advance the Southeast Stormwater Nature-Based Solution Trail Project. Following City Council approval, a working group including staff from TNC, Widseth, City of Alexandria, Douglas County, and Alexandria Public Schools formed and have continued to meet bi-monthly.

In October 2021, Ryan Noe presented preliminary results at the Minnesota Water Resources Conference to an audience of over 200 practitioners. The presentation attracted the interest of engineering consultants and communities considering applying for an upcoming Minnesota Pollution Control Agency (MPCA) grant. The MPCA grant provided funds for communities to assess their vulnerabilities to climate change, and specifically how to increase resilience to stormwater and reduce localized flood risk. In response to this grant, engineering consulting firms and other stakeholders proposed using the updated Atlas-14 estimates in their grant applications. Because applicants did not need to request preliminary data from us to write their application, we do not know how many applicants proposed using our data.

In direct communications with stakeholders applying for the grant, we produced preliminary results for the City of Austin. We also discussed the use of our data for proposals being prepared by a stormwater engineering consultant for the cities of Owatonna, Byron and St. Charles in southeast Minnesota. Discussions with the engineering consultant indicated they would use our estimates for 1-day, 100-year events as inputs into XP-SWMM models and use them to estimate stream flows based on design rainfall events in HEC-RAS for river restoration and floodplain modeling.

In February 2022, reviewers for the MPCA Community Resilience grant invited Ryan Noe to speak at the Minnesota Climate Adaptation Team meeting to describe the capabilities and availability of work produced from this project. The presentation raised awareness for the work and described its appropriateness for use in the grants they were reviewing.

During the project, Ryan Noe connected with Randy Neprash, a stormwater regulatory specialist with extensive contacts in the stormwater community. He volunteered to help distribute the final report and data to his networks which include the Minnesota Cities Stormwater Coalition, League of Minnesota Cities, City Engineers Association of Minnesota, Minnesota Association of Watershed Districts, and Minnesota Erosion Control Association.

Conclusions

Our work creates a proof-of-concept application of NOAA's Atlas-14 methods to dynamically downscaled climate change projects. We demonstrate that it is possible to approximate the magnitude and shape of NOAA's estimates, even with only 17 years of input data. Agreement between NOAA estimates and our modeled historical values was particularly good for 5- and 10-year recurrence intervals. Focusing on the duration-recurrence interval combinations with the best agreement with NOAA and examining the difference between modeled historic and end century high emissions scenarios shows a 20 to 30% increase in precipitation depth for central and northern Minnesota (Tables 1, 2).

This work also illuminated many challenges, especially 100-, 50-, and 2-year recurrence intervals. We tested several assumptions to try to improve agreement with NOAA values. The most notable improvement came from treating the individual models as separate time series, effective increasing the length of our AMS, which decreased our overall error by eight percentage points. We also found the 1-day and other short duration estimates were systematically underestimated in our outputs. We developed a novel way of applying NOAA's smoothing function to better estimate these values. Further research using more refined climate models downscaling techniques is needed to examine if the more extreme values we estimated, such as those in the northwestern region of the state, can be attributed to our modeling techniques or changes in climate.

Despite the challenges, this work helps to address the growing demand for precipitation intensity estimates that incorporate climate change. Until authoritative estimates from NOAA are available, some groups are using arbitrary increases. This work offers an informed interim estimate, but more importantly, creates new tools and techniques for addressing the question of climate change in precipitation intensity measurements.

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