Explaining Extreme Events of 2019 from a Climate Perspective

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EXPLAINING EXTREME EVENTS OF 2019 FROM A CLIMATE PERSPECTIVE

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Cover: Ruins and rubble are all that are left of homes destroyed by Hurricane Dorian viewed from a U.S. Customs and Border Protection rescue helicopter 5 September 2019 in Marsh Harbour, Abaco, Bahamas. Dorian struck the small island nation as a Category 5 storm with winds of 185 mph. (credit: Planetpix/Alamy Stock Photo)

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Anthropogenic Influences on Extreme Annual Streamflow into Chesapeake Bay from the Susquehanna River

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2019 water-year mean streamflow into Chesapeake Bay from the Susquehanna River was the third highest since 1891. Anthropogenic climate change has increased the probability of extreme Susquehanna River mean streamflows.

Averaged over the 2019 water year (1 October 2018 to 30 September 2019), freshwater discharge into the Chesapeake Bay was the largest since measurements began in 1937 (USGS 2019), and streamflow in the Susquehanna River, the largest tributary of the Chesapeake Bay (Fig. 1a), measured at Harrisburg, Pennsylvania (USGS station 01570500) was the third highest since records began in 1891 (Fig. 1b). These extreme anomalies in Susquehanna River streamflow can impact upper Chesapeake Bay salinity, temperature, turbidity, and biogeochemistry. Consequently, valuable living marine resources such as blue crabs (Jensen and Miller 2005), striped bass (Millette et al. 2020), and oysters (Kimmel et al. 2014) can be impacted, either positively or negatively, by these streamflow extremes.

While 2019 was the third highest mean streamflow in the Susquehanna, the all-time record was set in 2011, and the second highest was observed in 2004. This sudden

Fig. 1. (a) Map of the Susquehanna River, the stream gauge at Harrisburg (star), and the upstream watershed (shaded). (b) Time series of observed water year mean streamflow at Harrisburg. Red star denotes 2019, and the dotted line shows the threshold for an extreme event used in this study. (c) Comparison of water-year (WY) mean streamflow predicted by the water balance model driven by Livneh data vs the observed mean streamflow during the calibration period (1971–2011). (d) Comparison of probability distributions from the observations and Livneh-driven water balance simulation during the calibration period.

run of record events is consistent with recent increases in precipitation totals and extremes in the mid-Atlantic and Northeast regions of the United States (Guilbert et al. 2015; Hoerling et al. 2016; Howarth et al. 2019; Huang et al. 2017, 2018; Knutson and Zeng 2018). In the U.S. Northeast, climate models commonly project increased annual and extreme precipitation as a result of anthropogenic climate change (ACC) (Lynch et al. 2016; Ning et al. 2015). ACC has already increased the risk of extreme precipitation events and totals in the U.S. Northeast (Winter et al. 2020) and has likely increased annual and seasonal-mean precipitation over 1901–2010 (Knutson and Zeng 2018). A natural question, then, is whether any change in the frequency of extreme streamflow can be attributed to ACC. This attribution is complicated by a concurrent greenhouse gas-driven warming that, in isolation, would increase evapotranspiration and reduce runoff and streamflow (Knutson et al. 2013; Vose et al. 2017).

In this study, we use a water balance model to attribute the combined effects of changing mean temperature and precipitation on water year mean streamflow in the

Susquehanna River. We use simulations from phase 6 of the Coupled Model Intercomparison Project (CMIP6) to compare the probability of an extreme streamflow year like 2019 with the probability in a counterfactual climate without anthropogenic changes in radiative forcing. Using the water balance model also allows a separation of the effects of changing precipitation and temperature on extreme streamflow risk.

Data and methods.

Streamflow in the Susquehanna River at Harrisburg, Pennsylvania, was simulated from CMIP6 climate model data using a water balance model that predicts monthly mean runoff from monthly total precipitation and potential evapotranspiration (Wolock and McCabe 1999; McCabe and Markstrom 2007). Our use of the model was similar to Muhling et al. (2018), except we used the Hargreaves–Samani method (Hargreaves and Samani 1982, 1985) to calculate potential evapotranspiration (E_p) from climate model temperature data rather than the Hamon (1961) method. The Hargreaves–Samani method has a sensitivity to warming that is more consistent with non-water-stressed evapotranspiration calculated during climate model simulations (Milly and Dunne 2016, 2017). The water balance model was calibrated for the Susquehanna River basin by adjusting the model parameters for evapotranspiration, rain/snow mixing, runoff, soil storage, and snowmelt and underestimation using an optimization algorithm to minimize the root-mean-square error (RMSE) of monthly mean streamflow when using the last 41 years (1971–2011) of the Livneh et al. (2013) gridded temperature and precipitation observations as input. All water balance simulations predicted total runoff at a monthly time step, which is sufficient for capturing extremes in water year mean streamflow for a large river basin like the Susquehanna. Total runoff was converted to mean streamflow by integrating the time rate of runoff over the watershed area.

We ran an ensemble of water balance model simulations using climate model data from CMIP6. We used 52 ensemble members from eight different climate models that participated in the Detection and Attribution Model Intercomparison Project (DAMIP) (Gillett et al. 2016) and provided the output needed to calculate E_p (see Table ES1 in the supplemental information). The model temperature and precipitation data were averaged over the Susquehanna River basin upstream of Harrisburg and corrected for biases using the quantile delta mapping (QDM) method (Cannon et al. 2015) with the Livneh et al. (2013) gridded data used to calibrate the water balance model as the reference for the bias correction. As a result, the water balance model did not need to be recalibrated to run with the bias-corrected climate model data.

To calculate the present-day probability of an extreme water-year mean streamflow (P_i), we 1) set a threshold value of $1,509 \text{ m}^3 \text{ s}^{-1}$, the value observed in 1891 and that water years 2004, 2011, and 2019 have exceeded; 2) fit a gamma distribution to the pooled water-year mean streamflows simulated by models following the combined CMIP6 historical and SSP245 scenario for a 41-yr period centered around 2019 (1999 to 2039); and 3) calculated the probability of an extreme streamflow year above the $1,509 \text{ m}^3 \text{ s}^{-1}$ threshold using the fitted distribution. To determine the probability of an extreme streamflow in a counterfactual climate (P_o), we repeated the same process using streamflow simulations from models following the last 41 years (1974 to 2014) of historical forcing from the hist-nat scenario, which includes the historical time series of natural solar and volcanic forcings but excludes anthropogenic emissions. Extensions of the hist-nat scenario into the future, which would be necessary to center the hist-nat simulations around 2019, are not available for most models, but centering is less important than for the historical scenario because the natural forcing does not contain large anthropogenic trends. We then calculated the risk ratio as P_i/P_o and the fraction of attributable risk as $1 - (P_o/P_i)$ (Stott et al. 2016). A confidence interval for the risk ratio was determined using bootstrapping and a significance level of 0.1. The significance level and 41-yr time period were chosen to provide sufficient power to test our hypothesis. A posteriori tests using shorter or longer time periods showed that

confidence intervals in the results would change but the conclusions generally would not. The conclusions are also not sensitive to the definition of the threshold for an extreme event.

As an additional assessment, we also report results derived using a nonparametric approach described in Paciorek et al. (2018) with confidence intervals using the method of Koopman (1984). This approach has the advantage of not requiring an assumption about the probability distribution. However, whereas the gamma distribution method uses all available data to estimate the shape of the distribution and the probability of extremes, the nonparametric method relies only on the fraction of data points exceeding the extreme threshold and will have high uncertainty (Paciorek et al. 2018). As a result, the nonparametric method has significantly less power than the gamma fitting method (in other words, the nonparametric method is less likely to identify a real change in risk as statistically significant). We thus primarily rely on the gamma method, but present the nonparametric results for completeness and as a consistency check.

Finally, to separate the effects of changing temperature and precipitation on streamflow risk, we re-ran the water balance simulations driven by data from the hist-nat scenario with climate change factors applied to only the temperature or precipitation data. These change factors were derived by calculating the mean difference or ratio between the 1999–2039 historical/SSP245 and 1974–2014 hist-nat scenarios for each climate model. For temperature, the difference was added to the hist-nat time series, and for precipitation, the hist-nat time series was multiplied by the ratio. For temperature, we also considered separately the effects of evapotranspiration and the rain/snow ratio by applying the change factor to the data used to calculate E_p but not to the data used to apportion rain and snow, and conversely.

Results.

The water balance model accurately predicts historical water year mean streamflow when driven by observed temperature and precipitation (Fig. 1c). The streamflow simulation is essentially unbiased, highly correlated with the observations, and has a mean error [RMSE or mean absolute error (MAE); Fig. 1c] that is an order of magnitude less than the mean streamflow. We also used leave-one-out cross-validation, iteratively leaving one water-year of data out at a time and recalibrating and reevaluating the model, to test the robustness of the model calibration and predictive capability. This approach results in only a minor degradation of model predictive skill for the left-out year (RMSE of $77.5 \text{ m}^3 \text{ s}^{-1}$, MAE of $65.8 \text{ m}^3 \text{ s}^{-1}$, same correlation and bias), which confirms the robustness of our model. The observed and modeled streamflow can be well represented by a gamma distribution (Fig. 1d), supporting our use of the more powerful gamma method as our primary attribution test. Because the internal climate variability in the CMIP6-driven water balance model simulations is not in phase with the observed internal variability, we cannot directly compare these simulations with the observed time series. Instead, we use the Kolmogorov–Smirnov two-sample test to verify that the pooled streamflow simulations driven by the CMIP6 GCMs under the combined historical and SSP245 scenario have a similar probability distribution to the observed water-year mean streamflow. This test confirms that the distribution of simulated streamflow is similar to the observed distribution during the full observational period of 1891–2019 ($D = 0.0893$, $p = 0.265$).

From the water balance model simulations driven by CMIP6 models, the gamma distribution method estimates that there was a 2.52% chance of exceeding the threshold of $1,509 \text{ m}^3 \text{ s}^{-1}$ in a year with climate forcing similar to 2019 (Table 1). In the counterfactual scenario without anthropogenic emissions, this probability was lower at 1.63%, resulting in a risk ratio of 1.55 (90% confidence interval 1.23–1.92). The 90% confidence interval on the risk ratio excludes 1, so we conclude that anthropogenic climate change significantly increased the risk of experiencing an extreme water-year

Table 1. Probabilities of an extreme streamflow event in the counterfactual (hist-nat) and historical/SSP245 scenarios and the resulting risk ratio and fraction of attributable risk.

Method	P_0 (counterfactual)	P_1 (historical)	RR (90% CI)	FAR
Gamma	0.0163	0.0252	1.55 (1.23, 1.92)	0.355
Nonparametric	0.0164	0.0197	1.20 (0.828, 1.74)	0.167

mean streamflow in 2019. The best estimate of the fraction of attributable risk is 0.355, indicating that about 1/3 of the present risk of streamflow extremes is attributable to anthropogenic climate change.

The nonparametric method, which has weaker power than the gamma distribution method, produces qualitatively similar but less confident results (Table 1). The nonparametric method gives a slightly lower historical probability of an extreme streamflow compared to the gamma method (1.97%) and a similar counterfactual probability (1.64%). The resulting risk ratio (1.20) and FAR (0.167) are lower, but the confidence intervals on the risk ratio are much wider and include 1. The consistency of streamflow data with the gamma distribution (Fig. 1d) supports our reliance on the more powerful gamma method as the primary quantitative test, with the qualitative consistency between the gamma and less powerful nonparametric approach providing no reason to reject this result.

In Fig. 2, we compare the separate effects of modeled temperature, evapotranspiration, and precipitation changes on simulated streamflow. In the CMIP6 models, the most robust signal of anthropogenic climate change in this region is a rapid warming beginning in the 1980s and projected to continue into the future (Fig. 2a). In the absence of any precipitation changes, this warming would have reduced the risk of an extreme streamflow event (orange bar in Fig. 2b) by increasing evapotranspiration (blue). In the water balance model, temperature is also used to determine the rain/snow mixing ratio, and warming shifts the winter ratio toward rain, but this is modeled to have had a negligible effect on water year mean streamflow extremes (purple). Modeled precipitation begins to increase around the same time as temperature and emerges above the range of natural variability around the end of the historical experiment (2014). When considering the 41-yr window centered on 2019, the overall projection is for mean precipitation above the 1974–2014 natural baseline, which alone would cause a significant increase in the risk for extreme streamflow (green bar in Fig. 2b). Finally, the gamma and nonparametric methods yield similar results for each experiment, although the nonparametric results have much wider confidence intervals.

Conclusions.

Three extreme annual mean streamflow events have occurred in the last two decades in the Susquehanna River, and we found that ACC has increased the probability of these extreme events. In the model simulations, the increased risk from higher precipitation has exceeded the reduced risk from increased evapotranspiration. This attribution may be useful for guiding management decisions; for example, the Susquehanna River typically accounts for around half of the freshwater discharge into Chesapeake Bay, so an increased risk of extreme streamflow in the river may increase the risk of poor water quality and shifts in fish habitat in the bay. Similarly, the Chesapeake Bay Program supports efforts to improve stream health and function throughout the Susquehanna River watershed. Given the likelihood for increases in extreme mean streamflow events, it is important to consider their impact on the siting and design of stream restoration projects to ensure long-term success and improved effectiveness under changing climate conditions.

There are several limitations of our analysis. Tropical cyclones have contributed to some recent extreme precipitation and streamflow events in the study region (Huang

Fig. 2. (a) Time series of model mean temperature, precipitation, and water balance simulated streamflow under the two climate forcing scenarios. (b) Separate effects of changing temperature and precipitation on streamflow risk. Experiment “T change” accounts for the effects of warming on both evapotranspiration and rain/snow mixing ratios, while experiments “EP change only” and “Rain/snow change only” capture the effect of warming only on the respective factors.

et al. 2018), but any changes in these storms are unlikely to be captured in the coarse resolution global climate models examined here (van der Wiel et al. 2016). Potential and actual evapotranspiration are complex functions of many factors including temperature, radiation, and wind. The value of E_p is typically approximated using a few reliable climate model variables, such as the monthly mean minimum and maximum temperatures used by the Hargreaves and Samani (1982, 1985) method in this study. Other methods, like the Hamon (1961) method, assume that E_p can be approximated solely by monthly mean temperature, and experiments showed that this method would flip the streamflow risk ratios (see Table ES2). However, methods that use only mean temperature exaggerate the drying effect of warming (Milly and Dunne 2017; Seong et al. 2018), in part because they do not account for reductions in stomatal conductance as atmospheric CO_2 increases (Milly and Dunne 2016). While the Hargreaves–Samani (H-S) method also fails to account for stomatal changes, it does use the diurnal temperature range to modulate solar radiation, making its sensitivity more reliable than methods that only use mean temperature, and in our study region, the H-S method predicts a similar response of potential evapotranspiration to climate change as methods that do account for radiation, winds, and humidity (Milly and Dunne 2017). We did not apply weighting to account for the varying ensemble sizes of the CMIP6 models used in this study, so our results are heavily influenced by CanESM5 and other models that contributed more runs. However, considering several model subsets with equal distributions of ensemble size would not change our conclusions (Table ES2). We did not consider the effects of changes in land use, reservoir storage, or consumptive

use, all of which likely had a small effect on annual mean flows to the Chesapeake Bay (e.g., Najjar 1999). The effects of changes in precipitation intensity and frequency at submonthly time scales are also not included. However, the observation-driven water balance model was able to accurately simulate the 1971–2011 calibration period without considering these changes.

Several of the potential limitations to this study also suggest fruitful areas for future research. Our confidence about changes in hydrological extremes can be improved by research into the uncertainty contributed by the choices of potential evapotranspiration formula, climate models and scenarios, and bias correction and downscaling algorithms. Although the monthly water balance model performed well, more sophisticated hydrological models could account for changes in variables other than temperature and precipitation, such as wind speed, and could be used to attribute changes in extremes in smaller watersheds and rivers. Finally, we found that the gamma and nonparametric attribution methods for determining probability yielded similar results but disagreed about whether the identified increase in the risk of extreme streamflow is statistically significant; future work would benefit from additional research into hydrological extreme event attribution methods.

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