PROJECTING PLANNING-RELATED CLIMATE IMPACT DRIVERS FOR APPALACHIAN PUBLIC HEALTH SUPPORT

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ABSTRACT

Climate change is impacting the intensity, duration, and frequency of climatic events. With climate change comes a multitude of adverse conditions, including extreme heat events, changes in disease patterns, and increased likelihood and frequency of natural disasters, including in places previously not exposed to such conditions. Human health has foundations in the environment; therefore, these adverse climatic conditions are directly linked to human health. Rural communities in Appalachia are likely to experience negative consequences of climate change more severely due to unique geomorphology and sociopolitical realities of the region. Non-governmental organizations (NGOs) throughout the Appalachian region are currently working to build resilience and prepare for potential adverse effects from climate change. To aid in this process, projections of future climate scenarios are needed to understand possible situations and adequately prepare. In partnership with Ohio University and West Virginia University, this study aims to characterize potential future climatic scenarios from publicly-available global climate models (GCMs) and prepare information to share with Appalachian communities.

Climate model information for this analysis was obtained from NASA's Coupled Model Intercomparison Project (CMIP6). All code for data processing and analysis was prepared using the open-source R programming language to support reproducibility. To confirm that models can accurately simulate Appalachian climatic conditions, CMIP6 hindcast simulations for precipitation and maximum temperature were compared to observed weather records from NOAA. Climate models over and underestimated average precipitation values depending on location, while models consistently underestimated extreme precipitation values, simulated by total five-day precipitation. For temperature, climate models consistently underestimated average and extreme high temperature indicators.

For Appalachian region projections, three towns of interest (one for each state involved in the study: Virginia, West Virginia, and Ohio) were selected based on current community resilience efforts. In these locations, mid-century (2040 – 2064) and end-of-century (2075 – 2099) projections for precipitation and temperature were summarized under a low and a high emissions scenario. Increases in precipitation and temperature were observed under average and extreme scenarios; these increases were noticeably more extreme under higher emissions scenarios. These trends are consistent with other studies and climate science consensus. When compared to hindcast values, observed average precipitation values were overestimated and underestimated, while observed extreme precipitation indices, average temperatures, and heat wave indices were underestimated by GCMs. Context with observed data is important to understanding model accuracy for the Appalachian region. GCMs are a useful tool to project potential future climate scenarios at specific locations in the Appalachian region, though model data is best used to communicate general trends rather than as inputs for other physical models.

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GENERAL AUDIENCE ABSTRACT

Climate change is driving previously unseen changes in many aspects of the environment. Among these aspects, and of particular concern, are increased precipitation and increased high temperatures, which have direct negative outcomes on human health. Climate change can impact human health in a variety of ways, such as increasing instances of heat-related illnesses like heatstroke, changing insect-carried diseases patterns (i.e. Lyme disease, malaria), worsening preexisting conditions like asthma, and increasing the likelihood of natural disasters like flooding. Climate change also impacts mental health, especially increasing instances of anxiety and post-traumatic stress disorder from disasters. Rural communities like Appalachia are more likely to experience severe negative outcomes due to lack of resources, remote location, and economies historically based on resource extraction. Appalachia specifically also faces unique challenges with flooding, as many towns are situated in valleys with streams or rivers running through the center of town.

To address and prepare for possible climate change outcomes, community-based planning is required to build resiliency. Throughout many areas, but specifically in Appalachia, many community-based organizations are already working to strengthen their communities by providing stable housing, addressing flooding, and preparing emergency response teams. To aid in these efforts, information about potential future climate is beneficial to these organizations to understand and prepare for potential conditions. This study aims to use publicly-available climate models to generate information about possible future climate conditions to be shared with community organizations. Additionally, this project's datasets and procedures are publicly available, so this analysis can be performed by communities anywhere in the world given they have adequate computing power.

To check that models are a good indicator of previous climate conditions, and therefore would be useful for future projections, historic projected climate model outputs were compared to observed weather data. After confirming that the models used were fairly consistent with observed data, projected values for midcentury (2040 – 2064) and end-of-century (2075 – 2099) were gathered for Appalachian towns with interested community organizations. Projected values show increases in high temperatures and precipitation throughout the Appalachian region, including in short-term event scenarios, which is consistent with other climate science. Higher emissions scenarios result in greater increases in average and extreme temperature and precipitation values. Climate models can be a useful tool in understanding potential general climatic trends for a specific location and can support climate science communication.

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1. INTRODUCTION

Anthropogenic climate change is projected to influence the spatial and temporal distribution of individual weather and climatic events, as well as the intensity, duration, and frequency (Field & Intergovernmental Panel on Climate Change, 2012). For example, as temperature increases, the available water holding capacity of the atmosphere is predicted to increase exponentially; this corresponds with an increase in precipitation volume for a single storm, which can result in flooding and/or infrastructure damage (Min et al., 2011). Projected changes in temperature and precipitation are likely to result in negative outcomes globally on environmental health, including more frequent heat waves, increased magnitudes and frequencies of floods, declining air quality, longer drought periods, and more widespread vector-borne diseases (Balsari et al., 2020; Campbell-Lendrum & Corvalán, 2007).

Adverse impacts of climate change, including natural disasters, are likely to be particularly intense for rural communities given that they are often characterized by higher vulnerability and lower socio-economic status (Shinn & Caretta, 2020). Vulnerability is closely coupled with a community's adaptive capacity, i.e., the ability of a community to respond to hazard exposure. Communities with fewer private and public financial resources often have lower quality baseline infrastructure and have difficulty obtaining additional resources to support adaptation. Unfortunately, as lower socioeconomic status has been correlated with an increased likelihood of harm from extreme weather events (Shinn & Caretta, 2020), the health outcomes associated with climate change may worsen existing health disparities. Providing clear information on climate risks to vulnerable communities to aid in informed planning to address future concerns is necessary to increase resiliency (Cole et al., 2023; Ruane et al., 2016).

Within the United States, the predominantly rural Central Appalachian region is home to longstanding health and infrastructure inequities, which compound vulnerability to extreme weather events associated with climate change. The topography of the region predispositions communities located in valleys to flooding (Morrone, 2020), and creates unique water infrastructure challenges (N. Cook et al., 2015; Hubbart & Gootman, 2021; Hughes et al., 2005). As changes in temperature and precipitation evolve over time, changes in flooding in the Appalachia region will likely occur. Aging populations, elevated incidence of underlying health conditions, and inadequate health infrastructure may also render the Appalachian region particularly susceptible to heat waves (Curtin & Spencer, 2021; Leider et al., 2020; Morrone,

2020). Appalachia may not be as likely to experience temperatures as extreme as other areas of the United States, but changes in maximum and average temperatures could result in increased public health threats, including asthma (D'Amato et al., 2015). The Appalachian region has historically had a more temperate climate, so existing infrastructure may not include air conditioning to offset rising temperatures.

Increasing resiliency requires access to relevant information on climate risks to aid communities in informed decision making and planning to address future concerns (Cole et al., 2023); therefore, regional planning to reduce health impacts related to climate change can be supported by projections from climate change models. Several studies have used global climate models (GCMs) to look at changes in precipitation, with results indicating that high-intensity precipitation events will happen more frequently and that recurrence intervals for storms are changing, i.e. 50-year storms are now 25-year storms (Ha et al., 2020; Hong et al., 2021); however, the complexities of model development and the inherent uncertainty of forecasting can create challenges in communicating and utilizing projections from these models. Development of clear, culturally appropriate, and decision-relevant projections of extreme weather risks within the Appalachian region is essential, particularly given regional sociopolitical realities. In order to support burgeoning efforts to prepare for future extreme weather events, the present study aims to understand the needs of Central Appalachian communities in preparing for extreme weather events and to provide informational resources for use in community-driven decision making.

2. LITERATURE REVIEW

2.1 Anthropogenic Climate Change and Human Health

There is scientific consensus that anthropogenic activity has caused warming of the planet, which is directly observable via data collected from the atmosphere, the oceans, and the land (Cheng et al., 2020; Liverman, 2007). This warming has, and will continue to, drive a variety of outcomes on weather patterns and general climate, including longer, more intense, and more frequent heat waves, increased frequency and severity of storms, and more frequent droughts (Cook et al., 2018; Marx et al., 2021; Rahmstorf & Coumou, 2011; Trenberth, 2011). Climate impacts all aspects of human life and society, including physical infrastructure, agriculture, natural-resource economies, tourism, food security, clean water access, and human and environmental health. Of critical interest to the present work is the recognition that human health has foundations in the environment, and climate shapes the environment. Climate change is undermining human health—physically and mentally—and places stress on public health systems (Frumkin et al., 2008; Palinkas & Wong, 2020).

2.1.1 Extreme Heat

Past research has documented an increase in the incidence of multiple adverse health outcomes directly linked to changes in climate. For example, and perhaps most obviously, the intensity, frequency, and duration of heat waves is of increasing concern as global temperatures rise. Exposure to extreme heat is linked to several negative human health outcomes, including heat exhaustion, heat stroke, and exacerbation of pre-existing conditions, especially lung conditions (i.e. asthma, chronic obstructive pulmonary disease, etc.). Heat-related illnesses also have negative outcomes on mental health and well-being (Ebi, Vanos, et al., 2021). Between the years of 2000 – 2004 and 2017 – 2021, heat-related deaths increased by 68%; this trend is consistent across the globe (Romanello et al., 2022). Human-health impacts of increased temperatures are largely based on infrastructure; places that are not equipped with air conditioning are also likely to see increases in heatstroke and other illnesses, as air conditioning is an important tool in combating heat-related morbidity and mortality (Davis et al., 2021); therefore, a two degree increase in average temperature can affect health in all locations, not just in extreme environments like deserts. A surge in heat-related illness disrupts public-health systems by causing spikes in patient volume, closing health centers ill-equipped to handle high temperatures, and/or reducing medical personnel through personal illness (Ebi, Vanos, et al.,

2021). For example, the 2021 heat waves in the Pacific Northwest saw average temperatures between 100°F - 110°F, with a record-breaking maximum temperature of 121°F (White et al., 2023). While higher temperatures have been observed in equatorial zones, the infrastructure of the Pacific Northwest is unsuited to extreme temperatures: many residences and businesses do not have air conditioning, since temperatures in this region do not usually require indoor cooling. From June 25, 2021 – June 30, 2021, hospitals in Washington, Oregon, Idaho, and Alaska saw a 69% increase in emergency room visits for heat-related illnesses compared to the same time period in 2019. Businesses and workplaces in Canada were advised by the Workplace Safety Board of British Columbia to close businesses and office buildings if they were not equipped with proper air conditioning (White et al., 2023).

2.1.2 Vector-borne Diseases

Changes in global temperatures are also changing disease patterns, particularly vector-borne disease patterns. Around the world, there have been increased instances of vector-borne disease, including Zika virus, West Nile virus, Malaria, and Lyme disease, among others (Rocklöv & Dubrow, 2020). Climate change is and will continue to change patterns of disease, especially vector-borne diseases due to their strong ties to the environment. Since most insect vectors—i.e. ticks and mosquitos—are ectotherms, longer periods of warm weather will likely increase the abundance and feeding-activity of insect vectors, thus increasing disease transmission rates (De Souza & Weaver, 2024; Rocklöv & Dubrow, 2020). Changes in precipitation patterns may also increase the rates of vector-borne disease transmission, since wetter conditions can provide more favorable conditions for insect reproduction and larvae development (De Souza & Weaver, 2024). In addition to changes in areas where vector-borne diseases are present, currently in equatorial regions, there is expected to be an expansion of vector-borne diseases into previously temperate areas where insect vectors, historically, were less common (Lipp et al., 2002). Challenges with vector-borne diseases become more complicated when additional hosts are involved; for example, ticks that carry Lyme disease feed on rodents for their first blood meal, so changes in rodent populations would also change Lyme disease distributions (De Souza & Weaver, 2024; Rocklöv & Dubrow, 2020). Changes in disease patterns will compound the negative health outcomes stemming from climate change on top of physical health effects directly linked to extreme climatic conditions.

2.1.3 Natural Disasters

Exacerbating and compounding existing morbidity, mortality, and healthcare delivery challenges, natural disasters are expected to increase as climate continues to change. Intense precipitation, intense storms, and heavy flooding are increasing in frequency and expected to continue increasing over time (Ebi, Vanos, et al., 2021; Romanello et al., 2022). During recent severe storms like hurricanes Katrina, Harvey, and Sandy, the intense precipitation can be attributed to anthropogenic climate change, and these levels of precipitation are expected to become more common in the future (Emanuel, 2017; Lynn et al., 2009; Strauss et al., 2021). Flooding events and natural disasters can cause or compound other health effects, particularly due to infrastructure damage and disruption to public systems. After floods, there are often increased instances of injury and wounding, carbon monoxide or natural gas poisoning, infectious or parasitic diseases, waterborne and foodborne illness, skin or soft tissue infections, and exacerbation of noncommunicable or preexisting conditions (Ebi, Vanos, et al., 2021). In a literature review of 38 articles related to disasters, water-borne and vector-borne diseases were present in half of case studies looking at instances of flooding, n=31 and n=8 respectively (Lee et al., 2020). In general, natural disasters and extreme weather events magnify and highlight existing health issues and can introduce new health conditions to an area; as such, extreme weather events are important to anticipate in public health planning to build community public health adaptive capacity. For example, after hurricane Katrina in 2005, New Orleans changed their planning and response system to better anticipate extreme storm events, levee failure, and communication loss, lessons of which have been implemented into New Orleans' hurricane response plans (Colten et al., 2008).

2.2 Rural Communities and Extreme Weather Events

Rural communities are often more vulnerable to extreme weather events than their urban counterparts (Ristino, 2019; U.S. Global Change Research Program, 2018). While over 80% of America's population lives in urban areas, these populations are supported by food, grains, timber, minerals, and watersheds within rural areas; the long-term health and sustainability of rural communities therefore is necessary to maintain the foundation of an urbanized world (Ristino, 2019; Sharkey, 2009). Agricultural economies are heavily influenced by climatic patterns, which makes them more vulnerable to extreme weather events like prolonged heat, drought, and flooding (Ristino, 2019). In addition, multiple structural and geographic challenges

often result in significant rural health disparities, which render the rural communities even more vulnerable to climatic disruptions. Perhaps most critically, the distance between residential areas and essential services is greater in rural areas than in urban areas. Rural residents often need to travel three to four times as many miles for hospital-based healthcare than their urban counterparts, and rural grocery stores tend to be clustered, leaving certain areas without access to affordable, nutritious food (Holm et al., 2023; W. C. Miller et al., 2016; Shabo & Friedman, 2022). Despite these vulnerabilities, national polls and focus groups show that rural populations tend to be less concerned about climate change than their urban and suburban counterparts, and rural voters typically rank climate change as one of the least important environmental issues. In a poll of Midwestern voters, only 21% of rural voters placed climate change as one of the top two most pressing environmental issues compared to 36% of voters in urban and suburban areas (Diamond et al., 2020); however, despite these challenges, many rural voters—particularly young rural voters—support policies that address climate-related issues and support climate-change adaptation, including improving water and soil quality, reducing pollution from factories and powerplants, and strengthening rural communities against extreme weather events (Diamond et al., 2020). This presents an opportunity for better communication and information distribution around climate-related issues. Generally, rural communities are most receptive to clear communication that is relevant and applicable to their communities, particularly messages that include themes of environmental conservation, "win-win" solutions, and/or concern for future generations (Diamond et al., 2020).

2.3 Rural Communities in Appalachia

The Appalachian region faces unique challenges regarding climate-change-driven extreme events and natural disasters. Generally, challenges exacerbating extreme weather event and disaster recovery fall into two categories: sociopolitical and geographical. Appalachia's economy has been historically based on resource extraction. Appalachia, particularly Central Appalachia, is rich with natural resources, including timber, thermal and metallurgical coal deposits, and natural gas; however, much of the economic stress in the area has been attributed to natural resource extraction without a return of wealth to local communities (Eller, 2013), i.e. "boom and bust" economic cycles and absentee land ownership have failed to create sustainable long-term economic foundations. Past infrastructure issues continue to compound challenges with economics and health. For example, interstate highway systems that connect major urban

areas essentially bypassed Appalachia during construction. These decisions created an area where the primary transportation infrastructure is mountain roads, so high-traffic volumes are incapable of entering the region and lower-quality roads make these rural area more susceptible to isolation and delayed response times during emergencies (Eller, 2013). Rural areas are shown to have significantly longer wait times for EMS services compared to national averages. In a study analyzing EMS data from records across the United States, the average response time from a 911 call to emergency-scene arrival is seven minutes; this number increases to 14 in rural areas, and 1 in 10 rural emergencies required over 30 minutes of waiting before EMS personnel arrived on the scene (Mell et al., 2017). In addition to challenges within rural areas, mountainous terrain further complicates travel. Mountainous terrain, which is abundant in Appalachia, is harsh, and can impact travel in several aspects. Roads in mountainous regions are typically narrow and near exposed rock outcroppings, so they can be slow to traverse or closed due to natural hazards; in places without roads, difficult terrain can make certain areas nearly impossible to access. Additionally, mountainous remote locations without roads may also be difficult to access via air due to unique atmospheric conditions over mountains like fog, winds, and atmospheric pressure. It can also be difficult to land air vehicles in mountainous regions, which traditionally have steep slopes and dense tree cover (Bohtan et al., 2015). Challenges with travel and rural EMS operations combine in Central Appalachia, making disaster response in this region particularly challenging.

The unique geography of the Appalachian region that makes the provision of infrastructure so challenging simultaneously also renders local communities more susceptible to natural disasters. Many of America's most tragic or damaging floods have occurred in the Appalachian region, including Buffalo Creek and the Johnstown flood (Morrone, 2020). Geographical characteristics of the Appalachian region make it particularly susceptible to extreme flooding and the associated negative health outcomes, like contaminated water supplies. The combination of communities located in valleys and a lack of capacity for response due to systemic issues combine to exacerbate flooding and associated health issues (Morrone, 2020). Additionally, removal of vegetation during logging and mining operations has changed water movement patterns throughout Appalachia. With less vegetation to mitigate impacts of heavy rains, runoff rates have increased, causing lower-elevation or downstream areas to be more flood prone, particularly in towns (Eller, 2013). Aging infrastructure in Appalachia, especially water

control structures, increases the risk of flooding-related disasters. Many dams and other water control structures in Appalachia are aging or not up-to-code. This increases the likelihood of "hybrid-disasters" (e.g. heavy rainfall compounded with dam failure), which can cause historic flooding levels of water to damage towns (Morrone, 2020). With the compounding socioeconomic and geographical challenges of the Appalachian region, it is understandable that, since 1953, over 2600 major disaster declarations have occurred in the Appalachian region due to particularly intense events and inadequate local response, leading to federal disaster declarations (Morrone, 2020).

2.4 Appalachian Relationships to Disaster Recovery

Community response and recovery from extreme weather events are driven by a community's vulnerability and adaptive capacity (Shinn & Caretta, 2020). Vulnerability is defined as the susceptibility of an individual or a group to harm, and is closely coupled with adaptive capacity (Turner, 2016). Adaptive capacity is defined as a community's likelihood of hazard exposure and the ability to adapt to that hazard, and it is closely coupled with access to financial resources and community physical (e.g. infrastructure) and socioeconomic (e.g. poverty rates) characteristics (Turner, 2016). The vulnerability and adaptive capacity of the Appalachian region, particularly Central Appalachia, is strongly defined by its unique demographics, history, and geographical landscape.

Financial resources are one of the primary factors contributing to a community's vulnerability and adaptive capacity. Having more expendable income means that individuals and communities can prepare, maintain, and repair systems or infrastructure that may be damaged in extreme weather events. Public funding is essential in community-based resilience; communities with higher incomes generate more tax revenue, which can be used to improve and maintain local infrastructure. Federal aid is another source of funding available in many extreme weather event scenarios; however, accessing federal aid for disaster recovery, particularly in the United States, can be challenging in rural areas. During the 2018 flooding in Grant County, West Virginia, the Federal Emergency Management Agency (FEMA) provided aid in the recovery efforts, but funding was not enough to completely cover costs for many damages to residential properties: for example, aid was often tied to homeownership, so renters were unable to access federal financial resources (Shinn & Caretta, 2020). Low-income individuals are more likely to be renters and are more susceptible to "cost-burden problems," i.e. low-income areas are much

more likely to experience challenges recovering from extreme weather events (Twiss & Mueller, 2004).

Not only is eligibility for financial aid an issue, but existing housing infrastructure itself can contribute to vulnerability as well. While homeownership in Appalachia is quite high, around 70% in most counties, nearly 20% of housing units are mobile homes. In addition, as of 2004, about 80% of housing units were built prior to 1980 with almost 20% of those units built before 1939 (Jones & Spencer, 2018; Twiss & Mueller, 2004). Mobile homes and older homes are more susceptible to damage from intense storms, so even in instances where residents own their homes, federal funds may not be enough to cover damages. Appalachia's average poverty rate sits around 17%, which is 2% higher than the national average, and Central Appalachia's poverty rate sits around 25% (Lane et al., 2018).

Unstable baseline infrastructure and inconsistent access to basic needs means increased vulnerability and lower adaptive capacity in communities, particularly rural communities, so damages can be longer-lasting when disasters happen. Baseline infrastructure in rural communities receives far less funding than urban areas, and emergency systems are smaller in rural areas, so they are more likely to be strained during disasters. Additionally, vulnerability of rural residents is far less likely to be noticed or gain media attention than vulnerability in populated urban areas (Cross, 2001). Small towns are also more likely to lose populations quickly after disaster, which can hurt disaster recovery efforts (Cross, 2014). Access to essential services like food, clean water, complete sanitation systems, stable income, and community resources are also closely tied to adaptive capacity (Turner, 2016). Appalachia has been consistently identified as a region of high water inequity; i.e. high rates of plumbing poverty and community water systems that consistently fail to meet basic Safe Drinking Water Act requirements (Deitz & Meehan, 2019). Food deserts are also common in rural Appalachia; many individuals rely on food banks to meet their nutritional needs due to far distances to grocery stores (W. C. Miller et al., 2016).

2.5 Fostering Community-Based Resilience

Local and community context are important when it comes to extreme event planning (Stern et al., 2023), and previous research has consistently emphasized the criticality of culture and place when addressing health in the Appalachian region (Behringer & Friedell, 2006). For example self-reliance and the ability to work with personal or familial resources is highly valued

within the region, which can prevent communities from reaching out for external aid when needed (Shinn & Caretta, 2020). Place and location of residence are often tightly coupled with a person's identity, so it is important to consider cultural context when sharing climate adaptation knowledge with communities (Barnett et al., 2021; Stern et al., 2023). Teaching communities self-efficacy strategies that incorporate new adaptation strategies into existing norms boosts confidence and builds community self-esteem (Barnett et al., 2021). For example, in response to climatic hazards, communities naturally find strategies to manage risks through local support networks; building upon these locally identified strategies is more sustainable (Adger, 2009). Incorporating resilience practices that are reasonable and that uplift communities are more likely to be durable and to remain in practice (Barnett et al., 2021; Z. J. Miller et al., 2023; Stern et al., 2023). Extreme weather events, particularly flooding, can undermine the confidence of a community, so uplifting communities after natural disasters is particularly important to maintain current adaptation strategies and confidence levels (Barnett et al., 2021). Diversified adaptation strategies generally result in higher levels of resilience, which can aid in confidence as well as reduce vulnerability (Keshavarz & Moqadas, 2021). In general, approaches that target multiple aspects, build confidence, engage communities, and are communicated clearly will resonate best with communities and are most likely to be successful, both in hazard mitigation and long-term efficacy.

Even communities with high adaptive capacity, though associated with high potential for change, sometimes fail to successfully implement changes (Adger et al., 2007). The Intergovernmental Panel on Climate Change (IPCC) acknowledges that there are gaps in knowledge that limit the ability to make well-informed decisions about climate adaptation, which can include topics like physical changes, best policies, infrastructure interactions, and social impacts (Adger et al., 2007). While climate change is often regarded with skepticism in rural communities (Morrone, 2020), many voters support policies that address the negative outcomes from these events (Diamond et al., 2020). For example, 52% of rural Republican voters in the Midwest reported that environmental issues were important compared to just 36% of rural Republican voters who believe it is important for climate change to be addressed (Diamond et al., 2020). Additionally, based on Climate Opinion Factsheets from Yale's Program on Climate Change Communication, over half of the public in Ohio, Virginia, and West Virginia—three Central Appalachian states—believes that climate change is happening. Moreover, in these three

states, over two-thirds of the public supports policies addressing climate change, including incorporating climate change topics into public school curriculums, providing tax rebates for solar panels or energy-efficient vehicles, and funding research for renewable energy (Marlon et al., 2022a, 2022b, 2022c). Support for climate action is also generally higher among younger generations, including in rural areas.

Response to extreme weather events requires constant learning from communities, stakeholders, and governments. Research regarding the effects of atmospheric CO_2 concentrations and impacts on climate aspects like precipitation and temperature is important to making informed decisions about climate change (U.S. Global Change Research Program, 2018). Sharing knowledge with decision-makers is key to translating adaptive capacity into implementing change related to extreme weather events (Ristino, 2019). Studies find that one key aspect of leading successful climate adaptation workshops is having "the right people" in the room, including those with power and those impacted (Stern et al., 2023). Studies show that practical, clear, and concise messaging from *trusted sources* is best received by rural communities when discussing adaptation to extreme weather events (Barnett et al., 2021; Diamond et al., 2020; Z. J. Miller et al., 2023). For example, a recent poll of Midwestern voters found higher trust in USDA rather than EPA on environmental issues, though both are federal agencies with access to the same frontline climate science research (Diamond et al., 2020). Among environmental issues, Midwestern voters in the United States ranked climate change as least important, preferring to address more visible environmental issues like ensuring clean air and water (Diamond et al., 2020). This preference for addressing visible issues through community-trusted organizations can provide an alternative approach for supporting communities to address negative outcomes stemming from climate change.

2.6 Global Climate Models as Planning Tools

GCMs aim to simulate potential future climate scenarios based on a variety of physical, atmospheric, and geospatial properties (Raju & Kumar, 2020). GCM outputs are discussed through the climate impact driver (CID) framework, which describes physical climatic components that impact elements of ecosystems or societies. CIDs are quantified using indices. CIDs alone do not entirely encapsulate consequences and must be coupled with vulnerability and adaptive capacity to quantify the full magnitude of climate impacts on a specific region (Ruane et al., 2022). GCMs, naturally, are complex and include a large range of uncertainty due to the

multitude of inputs and inherent complexity of simulating large and complex global systems. These large ranges of uncertainty may render climate models not particularly useful for short-term event simulation, but generally climate models can show trends that can be useful in long-term decision making and planning (Hayhoe & Stoner, 2021). Best practices for climate projections in decision-making include using a collection of models to capture natural variability while providing an idea of what future scenarios may look like (Hayhoe & Stoner, 2021), as well as comparing hindcast model outputs with observed data for validation (Raju & Kumar, 2020). Comparing model hindcast simulations to observed data is an important step in understanding the inherent uncertainties present in climate models. Earth's atmospheric systems are complex, and since climate models are empirical and based on current observed conditions, no model can predict what future conditions will look like with 100% accuracy. Comparisons with observed data can help identify strengths and limitations with ensembles as a whole and the individual models within them. Despite limitations and uncertainties, models can play an important role in supporting planning for climate change and extreme events, so long as this information is used in context and with acknowledgement of uncertainties and variability (Hayhoe & Stoner, 2021; Raju & Kumar, 2020).

Community-level projects and local context are important for successful climate adaptation (Cole et al., 2023; Diamond et al., 2020); to aid in resilience efforts, providing information about projected future scenarios could be advantageous for more accurate planning. In fact, the previous iteration of the CMIP data (CMIP5) was used in a similar way by the public health department of Orleans County, NY. Orleans County published a Heat and Health report in 2019 detailing heat exposure and vulnerability. CMIP5 projections were used to quantify average maximum temperatures during the summer months under two emissions scenarios (NYDOH, 2019). Use of GCMs by a state department of health indicates that there could be interest in this information across other state entities or local organizations.

Both the IPCC and climate scientists agree that climate modeling and disaster resilience communities need to work more closely for planning under a wide range of emissions scenarios while addressing uncertainties to adequately adapt to changing climates (Raju & Kumar, 2020). For example, the United States Geological Survey provides the United States Department of Interior with climate science from GCMs, which is used to inform decision making about water quality and availability, land use, wildfire regimes, and invasive species management (Terando

et al., 2020). On a local scale, several studies have investigated future conditions using climate models intended for policy making, including in East Asia, India, and Iran (Hong et al., 2021; Mishra et al., 2014; Shiru et al., 2022). Specifically in the Appalachian region, one study has analyzed changes in rainfall over the eastern United States. This study observed increased precipitation values across the region, particularly under greater emissions scenarios and at the end-of-century (2076 – 2099) timescale (Fernandez & Zegre, 2019). In general, climate models can capture general trends that can be beneficial for long-term planning related to climate change (Raju & Kumar, 2020).

2.7 Present Study

The overall goal of this research is to develop summaries of projected changes for relevant CIDs in the North Central, Central, and South Central regions of Appalachia to aid in foundational climate resiliency planning. Relevant CIDs are informed by preliminary findings and discussions from listening sessions in the North Central, Central, and South Central Appalachian regions. During these listening sessions, public health officials, nonprofit, and local health department employees expressed concerns regarding extreme heat and flooding in the region. CIDs were selected to quantify extreme heat and precipitation, as these climate aspects are of interest to the region. These CIDs are used to compare the projected extreme weather events to their current conditions. CID hindcasts and projections are analyzed using outputs from climate projection data from NASA's Coupled Model Intercomparison Project (CMIP6) ensemble climate models. From the ensemble model data, the goal is to determine strengths, limitations, and biases in the CMIP6 data by comparing hindcast projections to observed climate data and to draw conclusions regarding projected spatial and temporal changes for relevant CIDs for the Appalachian region at the middle and end of the 21st century.

3. METHODS

3.1 Overview of Methods, Data Sources, and Integration

To ensure project data analysis was most relevant to selected communities, primary CIDs of interest were identified via multi-university listening sessions that invited local Appalachian nonprofits, health care workers, environmental managers, emergency responders, and relevant nonprofits. These listening sessions were hosted by Ohio University, with joint university institutional review board oversight by Ohio University, West Virginia University, and Virginia Tech (VT IRB#: 23-592). CIDs are defined by the IPCC as "physical climate system conditions that affect an element of society or ecosystems" (Ruane et al., 2022), and are intended to be neutral in connotation. CIDs are grouped by represented conditions and quantified by indices, such as "99th percentile daily precipitation" or "days above 95ºF" (Ruane et al., 2022). CIDs of interest were identified for the Appalachian region via the aforementioned listening sessions (results compiled by Kruse-Daniels, 2024). Three sentinel towns (one per each home state of each university: Pulaski, VA; Williamsburg, WV; and Nelsonville, OH) were identified as useful locations for climate forecast analysis (Figure 3.1). The three towns from each state were selected based on actions from non-governmental organizations (NGOs) currently running successful resiliency projects (Table 3.1) (Kruse-Daniels, 2024). Towns were selected based on the existence of active and interested community groups currently focused on planning adaptations to climate change. Relevant CIDs (temperature and precipitation) and their indices serve as the primary model outputs analyzed in subsequent project work.

Table 3.1 Appalachian towns, associated non-governmental organizations, and resilience actions

Location	**Local Organization Name**	**Current Resilience Strategies**
Pulaski, Virginia	Friends of Peak Creek	Flood resilience planning; community engaged programming; "Silver Jackets" local organization collaboration partnership; industrial legacy acknowledgement; industrial waste cleanup
Williamsburg, West Virginia	Williamsburg Area Response Team	Community-led, extreme-event-based response; vulnerable population focus; regularly-updated response plans
Nelsonville, Ohio	New Leaf Villages (original location)	Affordable housing; local workforce development; mental health support; sustainable materials; renewable energy; multiple locations

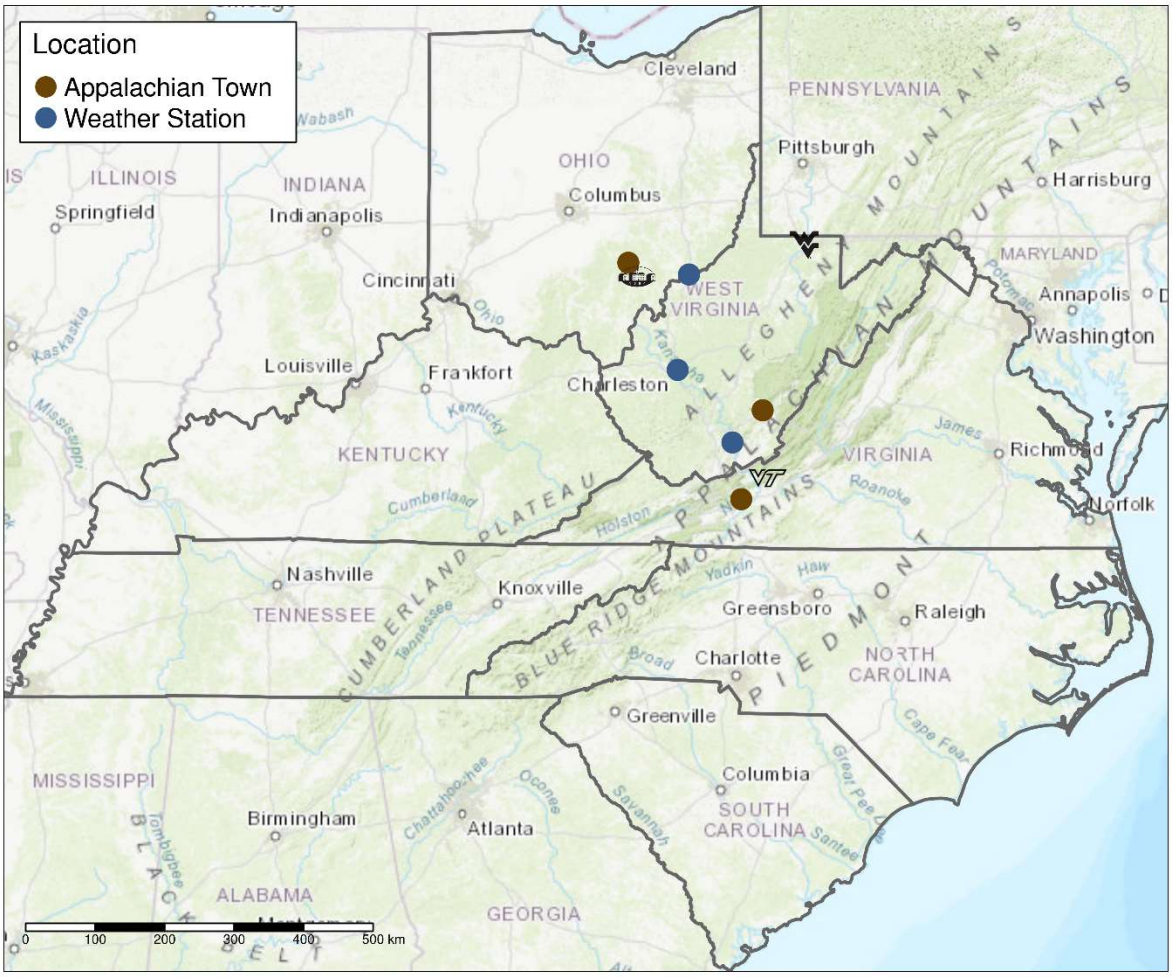

Figure 3.1 Appalachian towns and weather stations overlayed on spatial extent of data. Brown points show locations of "positive deviance" where local organizations are currently building resilience efforts; these towns' resilience efforts could benefit from climate projections. Blue points show locations of NOAA weather stations where model data was compared to observed data. Involved institutions are indicated by their logo.

Relevant model data was downloaded from output files of the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscale Projections (NEX-GDDP) generated by the sixth iteration of the Coupled Model Intercomparison Project (CMIP6). NASA's CMIP project operates under a Creative Commons license and is therefore publicly available for use (see data availability statement). Output files from the NEX-GDDP CMIP6 data set are rasters and were processed accordingly. Hindcast model outputs were compared to observed data from NOAA weather stations to confirm CMIP6 ensemble model outputs were applicable to the Appalachian region, as the unique local topography presents challenges to some

climate and weather models (Fernandez & Zegre, 2019). Finally, projected climatic conditions were summarized to understand what future climate may look like in the Appalachian region. All analyses were completed using R, version 4.2.2 (R Core Team, 2022), and RStudio (Posit Team, 2022). A flowchart of the steps for the analysis is shown in Figure 3.2.

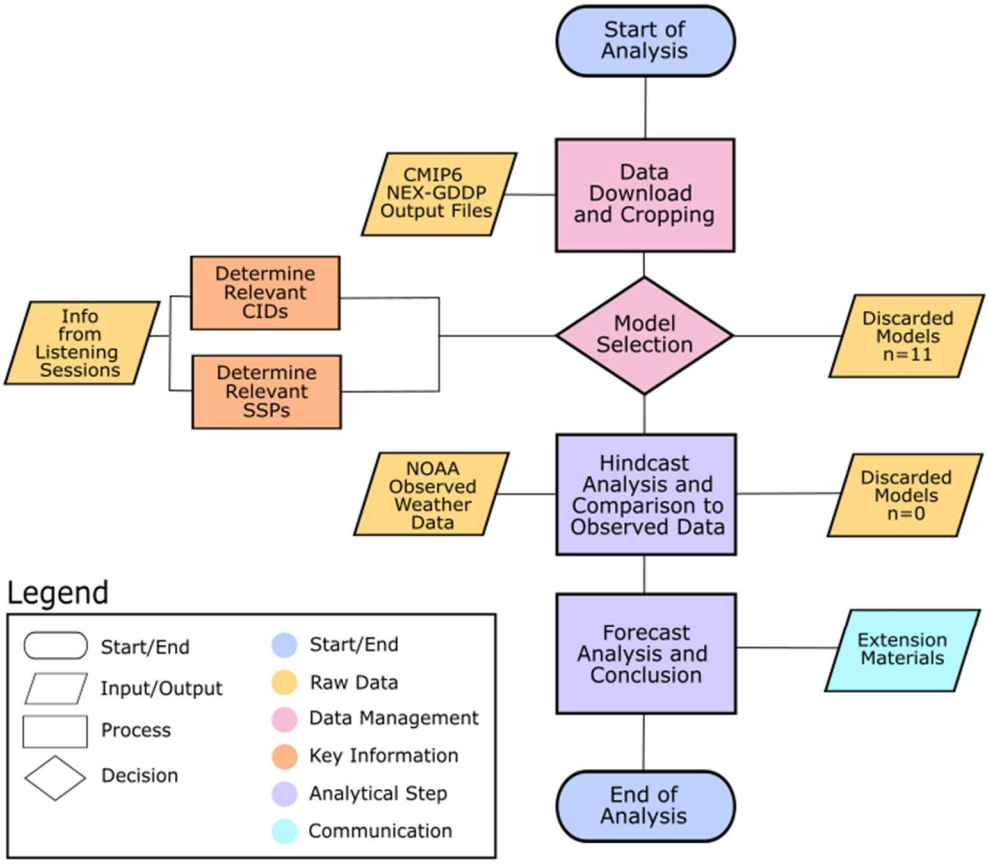

Figure 3.2 Methods process flowchart

3.3 Data Sources

3.3.1 Observed Meteorological Records

Observed weather data were obtained from NOAA's Global Historical Climatology Network daily data (GHCNd) (Menne et al., 2012). The GHCNd dataset includes daily data on a variety of weather conditions, i.e. temperature, precipitation, etc., at different locations around the world. Some stations report data back to as early as 1890, but most stations were established between 1950 and 1960 (NCEI, 2016). GHCN is currently active and receives daily updates from

reporting stations across the globe. The three GHCN weather stations used for hindcast comparisons were Parkersburg, WV; Charleston, WV; and Bluestone Lake, WV. These weather stations were selected for their proximity to the Appalachian towns of interest (Figure 3.1). The timescale for the hindcast comparison was 1970 – 2014.

3.3.2 Ensemble Climate Model Hindcasts and Projections

The climate models used in this analysis are output files from the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscale Projections (NEX-GDDP) generated by the sixth iteration of the Coupled Model Intercomparison Project (CMIP6). The project includes ready-to-use, bias-corrected output files from 35 unique GCMs, developed by various climate modeling centers from across the globe. The raster outputs are stored in netcdf format. Climate model outputs yield results for a variety of CIDs under a range of emissions scenarios, represented by "shared socio-economic pathway" (SSP) scenarios. SSP scenarios integrate social, economic, and political factors that influence greenhouse gas emissions, which are then used as inputs to GCMs to various future changes in temperature, precipitation, and other climate conditions (Meinshausen et al., 2020). Lower number SSPs indicate a lower emissions future, while higher numbers indicate higher rates of fossil fuel usage. Nine SSPs are recognized by the IPCC, and four are included in the CMIP6 data set: 1) ssp126, representing a low emission scenario; 2) ssp585, representing emission scenarios assuming fossil fuel growth; and 3) ssp245 and 4) ssp370, which represent middle-ground emission scenarios. All 35 models included in CMIP6 include outputs under the ssp585, as well as a hindcast scenario to compare with observed data. All but two models include outputs under the ssp126 scenario, and some models opt to omit one or both middle emission scenarios (ssp245 and ssp370).

3.4 Emissions Scenarios and Temporal Period of Projected Analysis

GCMs rely on different climate forcing methods based on different concentrations of atmospheric carbon dioxide. As future climate projections rely heavily on current policies, decisions, and actions that are difficult to predict, it is important to select multiple emissions scenarios to look at a variety of potential changes rather than selecting one emissions scenario. Additionally, climate models are best at showing long-term, general trends, so having multiple emissions scenarios for context provides more useful data. Because ssp126, a low emissions scenario, and ssp585, a high emissions scenario were included in all but two models in the

CMIP6 ensemble, these two emission scenarios were selected for analysis; they can be assumed to bracket a range of potential scenarios for climate change. Indices related to temperature and precipitation CIDs were analyzed over three periods: 1) hindcast data was summarized from 1970 – 2014; and future projections included two twenty-five year time periods 2) a midcentury period from 2040 – 2064 and 3) an end-of-century period from 2076 – 2100.

3.5 Ensemble Climate Model Data Acquisition

NASA's CMIP6 data set was obtained using the commands from the "httr" R package. The "httr" package uses curl principles, which is a command-line approach for data retrieval from URLs instead of a browser approach (Wickham, 2023). During the data acquisition process, the NEX-GDDP files were cropped to the Appalachian region (Figure 3.1) to save storage space and reduce processing time. Data downloads were performed using Virginia Tech's Advanced Research Computing system using R through the RStudio IDE.

3.6 Climate Impact Driver Quantification

Each CID was quantified using two indices: one representative of annual change and one representative of extreme weather events. In keeping with CID best practices, quantifiable metrics were selected to be representative of annual and short-term measures. Responses from listening sessions indicated that precipitation and extreme high temperatures were CIDs of significant and widespread interest. Two indices representative of average values and more extreme conditions were selected to communicate each CID (Table 3.2).

Table 3.2 Climate impact drivers and corresponding indices

	Average Index	**Short Term/Extreme Index**
Precipitation	Total Annual Precipitation [inches]	Maximum Five-day Precipitation [inches]
Maximum Temperature	Average Annual Maximum Temperature [degrees F]	Number of heat waves, defined as 2+ days over 90 degrees F [n]

Annual measures include total precipitation, as calculated via Equation 3.1 for one model, with the average across model represented by Equation 3.2.

$$P_{m,y} = \sum_{d=1}^{D=3} p_{m,d} \tag{3.1}$$

P = total annual precipitation in CMIP6 model m and year y

p = daily precipitation for model m on day d

$$P_y = \frac{1}{x}\sum_{i=1}^{x}\left[\sum_{d=1}^{D=365} p_{m,d}\right] \tag{3.2}$$

P = total annual precipitation average for year y across x CMIP6 models
p = daily precipitation for model m on day d
i = model index

The same calculations were performed for average maximum temperature via Equations 3.3 and 3.4.

$$T_{m,y} = \frac{1}{365}\sum_{d=1}^{D=365} t_{m,d} \tag{3.3}$$

T = average annual maximum temperature in CMIP6 model m and year y
t = daily maximum temperature for model m on day d

$$T_y = \frac{1}{x}\sum_{i=1}^{x}\left[\frac{1}{365}\sum_{d=1}^{D=365} t_{m,d}\right] \tag{3.4}$$

T = average annual maximum temperature for year y across x CMIP6 models
t = daily maximum temperature for model m on day d
i = model index

Short-term metrics were selected to be representative of extreme event scenarios. Extreme rainfall events that often cause flooding were simulated by total five-day rainfall per Equation 3.5.

$$P_{5_{m,y}} = \max_{d\in[5,365]}\left\{\sum_{d-5}^{D=365} p_{d,m}\right\} \tag{3.5}$$

P_5 = maximum 5 day precipitation in CMIP6 model m and year y
p = daily precipitation for model m on day d

Extreme heat events and heat waves were simulated by number of occurrences of two consecutive days above 90°F (NWS, n.d.-a). Changes in high temperatures can be more easily understood when communicated as number of heat wave events. Since no formal, universal

definition of a heat wave exists, the National Weather Service's heat wave definition was selected for this study. This calculation was performed via Equation 3.6.

$$F_{m,y} = \sum_{d=1}^{D=365} I_{t_{m,d}} \quad \begin{cases} I = 1 \; if \; (t_{d-1} \cup t_d) > 90 \\ I = 0 \; if \; (t_{d-1} \cup t_d) < 90 \end{cases} \tag{3.6}$$

F = total number of two-day heat wave events in CMIP6 model m and year y
t = daily maximum temperature for model m on day d
I = binary indicator

Due to model calculation limitations, it is important to note that this calculation counts the number of two day events regardless of the surrounding days. For example, three consecutive days above 90°F would be counted as two heat waves in these calculations, even though the NWS and other agencies would likely classify three consecutive days above 90°F as one heat wave.

3.7 Hindcast Analysis

Prior to use in forecast analysis, CMIP6 hindcast model outputs were compared with observed data closest to the three towns identified during the listening sessions to confirm applicability to the Central Appalachian region. For this comparison, temperature and precipitation data were pulled from NOAA weather stations to compare to model hindcast values. Locations for observed data were selected based on distance to the nearest town identified by Kruse-Daniels (2024) as a potential outlet for future climate communication and implementation of resiliency practices. In addition to distance, the three towns for projected analysis have a north-south gradient, so the weather stations selected reflected this geographical region. During value extraction, the points extracted in the GCMs were identical to the coordinates of the weather stations in Bluestone Lake, WV; Charleston, WV; and Parkersburg, WV (Figure 3.3, Table 3.2). Model results were compiled to compare both annual and short-term indices for precipitation and temperature. Annual analysis comparisons were used to determine outlier models that had to be discarded, since modeling short-term extreme events may yield naturally extreme results. One weather station, Parkersburg, WV, had two years of missing data due to the station being offline. This was addressed with the wide range of dates from 1970 to 2014, so two years of missing daily data was relatively minor in the averages. All averages for

observed values included a t-test 90% confidence interval to capture variability in averages throughout the region. While a hindcast to observed comparison can provide some insights to the accuracy of future projections, it is important to note there are limitations and assumptions to the hindcast comparison, particularly regarding assumptions with climate stationarity.

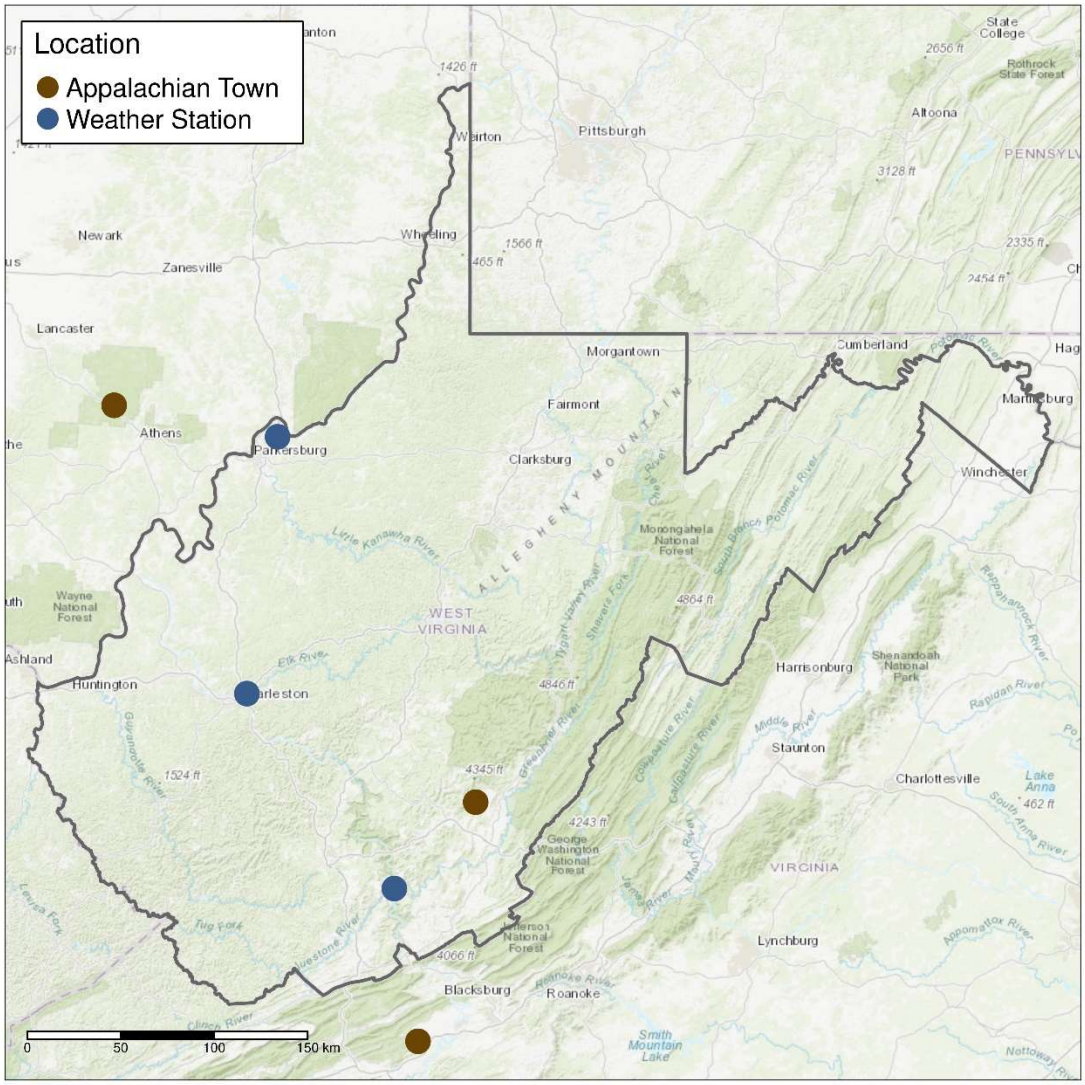

Figure 3.3 Locations of weather stations used for comparison of observed data to hindcast projections

3.8 Projected Analysis

Following the hindcast analysis, the projected future CID values were quantified for the low (ssp126) and high (ssp585) emissions scenarios for each model. Annual and short-term indices were analyzed for maximum temperature and precipitation. The projected analysis was

completed in the three Appalachian positive deviance towns based on information from listening sessions: Pulaski, VA; Williamsburg, WV; and Nelsonville, OH (Table 3.2). Hindcast and projected analyses were completed using point extractions on the CMIP6 raster files. Raster point extractions is a spatial technique that involves extracting raster files at specific locations (i.e. longitude and latitude). This allows data to be collected a specific locations of interest.

Table 3.3 Geographic information of selected analysis areas

Town	**State**	**Latitude**	**Longitude**	**Elevation (ft)**	**Relevance**	**Analysis Timeframe**
Bluestone Lake	WV	37.64199	-80.8828	424	Weather Station	1970 – 2014
Charleston	WV	38.3795	-81.5911	278	Weather Station	1970 – 2014
Nelsonville	OH	39.45626	-82.2291	702	Positive Deviant	2040 – 2064, 2070 – 2099
Parkersburg	WV	39.33948	-81.4438	245	Weather Station	1970 – 2014
Pulaski	VA	37.05917	-80.7690	1903	Positive Deviant	2040 – 2064, 2070 – 2099
Williamsburg	WV	37.9697	-80.4919	2192	Positive Deviant	2040 – 2064, 2070 – 2099

4. RESULTS

4.1 Final Models, SSPs, and Timeframes

Of the 35 CMIP6 Models included in the ensemble, 24 were included in hindcast and projected analyses: ACCESS-CM2; ACCESS-ESM1-5; BCC-CSM2-MR; CanESM5; CMCC-ESM2; CNRM-CM6-1; CNRM-ESM2-1; EC-Earth3; EC-Earth3-Veg-LR; FGOALS-g3; GFDL-ESM4; GISS-E2-1-G; INM-CM4-8; INM-CM5-0; IPSL-CM6A-LR; KIOST-ESM; MIROC-ES2L; MIROC6; MPI-ESM1-2-HR; MPI-ESM1-2-LR; MRI-ESM2-0; NESM3; NorESM2-LM; and NorESM2-MM. A total of 11 models were excluded due to missing temperature data, incorrect number of layers in the files, and outlier data acknowledged by the CMIP6 project (Table 4.2).

Table 4.1 Models excluded from CMIP6 analysis during the data download and initial assessment

Model	Reason for Exclusion
CESM2	No temperature data
CESM2-WACCM	No temperature data
CMCC-CM2-SR5	Data rejected by CMIP6 Project
GFDL-CM4 (gr1)	No ssp126 scenario
GFDL-CM4 (gr2)	No ssp126 scenario
KACE-1-0-G	Did not have 365 or 366 layers in files
HadGEM3-GC31-LL	Did not have 365 or 366 layers in files
HadGEM3-GC31-MM	Did not have 365 or 366 layers in files
IITM-ESM	No temperature data
TAI-ESM1	CMIP6 Project recognized high temp values and deviation from other models
UKESM1-0-LL	Did not have 365 or 366 layers in files

In addition to checking file characteristics, point extraction versus polygon extraction was examined for each index at each location and under each emissions scenario. Polygon extractions were performed at the county level. No extraneous values or stark differences were found between point versus polygon extraction (Appendix A). Since point extractions yielded reasonable results and are more accurate to a specific town, especially given the complex topography of Appalachia, point extractions were used in all hindcast and projected analyses.

4.2 Hindcast Comparison to Observed Data

4.2.1 Precipitation Comparison

Total annual precipitation outputs from the hindcast model projections were compared to the observed precipitation values at the weather stations (Figure 4.1). Hindcast projections were extracted the weather station coordinates for direct spatial comparison. Box plots are used to show the range of average precipitation values simulated across all GCMs included in the analysis, as well as observed average precipitation values taken from GHCN weather stations for the period from 1970 – 2014. The average total amount of rainfall in a year across the study locations ranges from 37.9 inches (with a 90% confidence interval of 36.6 to 39.3 inches) in Bluestone Lake to 44.6 inches (with a 90% confidence interval of 43.1 to 46.1 inches) in Charleston. However, the average annual precipitation in the GCM simulations was not always consistent with observed values. In Bluestone Lake, all of the climate models included in this analysis overestimated annual rainfall with an average observed total precipitation confidence interval ranging from 36.6 inches to 39.3 inches, and a model ensemble median of 41.2 inches (and a minimum projection of 40.6 inches). Conversely, all of the climate models underestimated rainfall in Charleston, with the model ensemble median of 42.6 inches and an observed confidence interval ranging from 43.1 inches to 46.1 inches. In Parkersburg, GCM simulations were more consistent with observed values, with the observed ranging from 37.5 to 43.4 inches; it is worth noting that Parkersburg has the widest 90% confidence interval around the observed value. The model hindcast spread falls completely within the confidence interval, with model hindcasts ranging from 40.7 inches to 41.8 inches. Including a 90% confidence interval around the mean observed annual precipitation, the model spread fell above the observed value for one location (Bluestone Lake, WV); the model spread fell below the observed value for one location (Charleston, WV); and the model spread fell within the range of observed values for one location (Parkersburg, WV). Overall, observed values were not greater than three inches of rain away from the median observed value. From these observations, it appears that the models are flattening precipitation variability across the region, which is important to note when using these models for any future decisions.

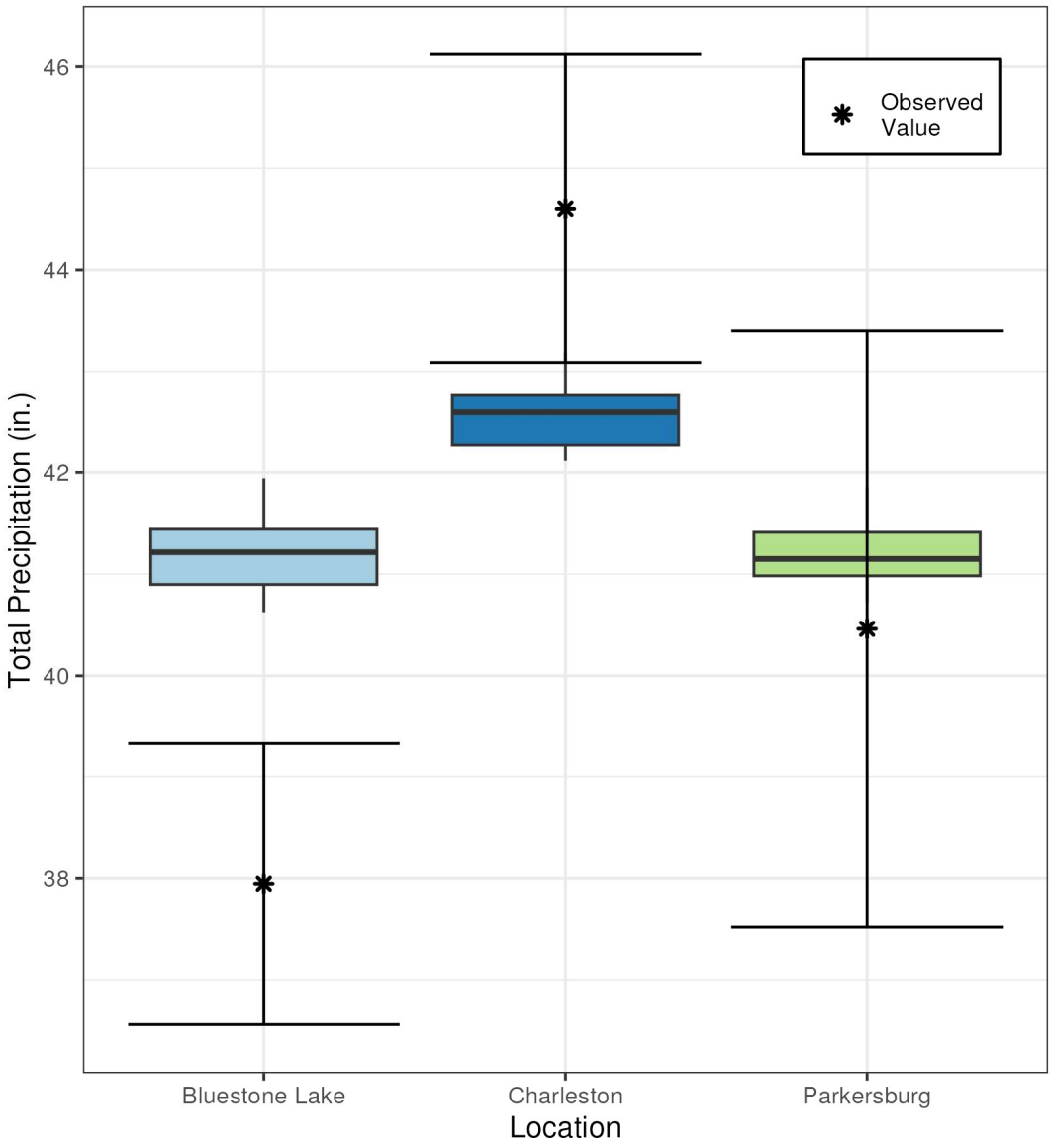

Figure 4.1 Total annual precipitation hindcast model outputs compared to observed data at three selected Appalachian weather stations: Bluestone Lake, WV; Charleston, WV; and Parkersburg, WV

To simulate extreme rainfall events, hindcast maximum five-day precipitation values were compared to observed maximum five-day precipitation values (Figure 4.2) using the same boxplot approach to capture the spread of hindcast scenarios compared to observed values. Unlike with the annual precipitation measures, where models overestimated and underestimated extreme rainfall, all models consistently underestimated the observed maximum five-day precipitation values at the three weather stations, Parkersburg, WV; Charleston, WV; and

Bluestone Lake, WV during the same hindcast period from 1970 – 2014. The spread of observed maximum five-day precipitation values across the West Virginia weather stations ranges from 3.26 inches in Bluestone Lake, WV (with a 90% confidence interval from 3.18 to 3.60 inches) to 3.73 inches in Charleston, WV (with a 90% confidence interval from 3.52 to 3.94 inches). The greatest distance between the median highest five-day precipitation value and the mean observed value was 1.13 inches in Charleston, WV, with a median model hindcast value of 2.60 inches and an observed mean value of 3.73 inches. This difference was 0.90 inches in Parkersburg, WV, with a median model hindcast value of 2.49 inches and a mean observed value of 3.39 inches, and 0.65 inches in Bluestone Lake, WV, with a median model hindcast value of 2.62 and a mean observed value of 3.26 inches. Models underestimating five-day maximum precipitation by 0.65 inches to 1.13 inches across locations is noteworthy regarding extreme precipitation metrics. There was one outlier model in Charleston, WV, that significantly underestimated the mean observed value, with one model estimating the five-day precipitation value at 2.0 inches, while the median hindcast value was 2.59 inches and the observed value was nearly 1.75 inches greater at 3.73 inches. However, even a underestimation like this outlier model projects precipitation values that could be significant enough to cause flood events. Also, interestingly, the 90% confidence interval around the observed five-day precipitation values is approximately the same spread as the hindcast models for five-day observed precipitation; had the hindcast projections been closer to the observed five-day precipitation values, this could indicate that a model spread could be a decent representation of the 90% confidence interval for observed precipitation.

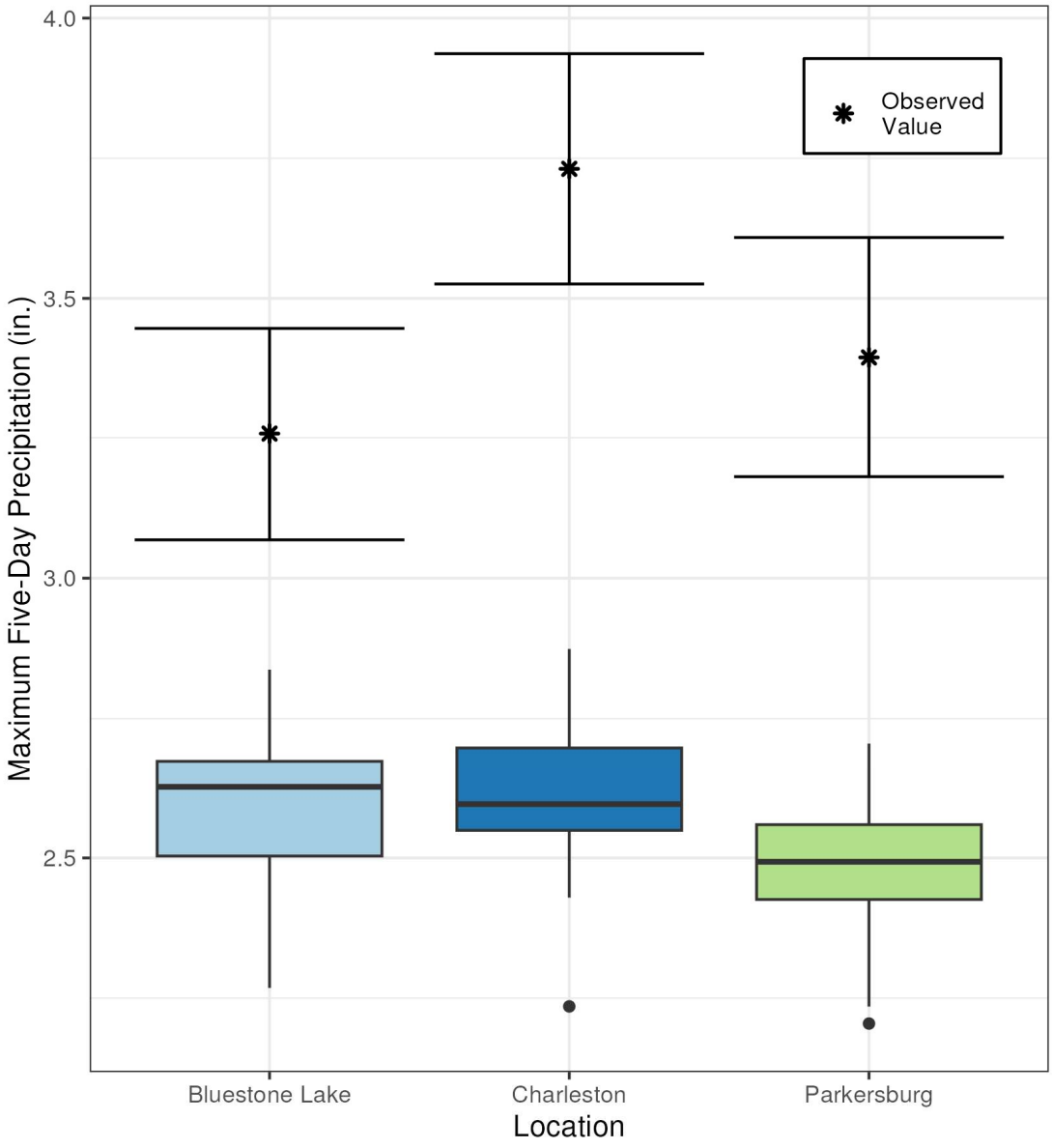

Figure 4.2 Maximum five-day total precipitation hindcast model outputs compared to observed data at three selected Appalachian weather stations: Bluestone Lake, WV; Charleston, WV; and Parkersburg, WV

4.2.2 Temperature Comparison

Average temperature model hindcast values were compared to the observed annual maximum temperature the three weather station locations (Figure 4.3); average temperatures capture the average of the highest temperature each day. Using the same approach as the precipitation comparisons, boxplots are used to capture the spread of models compared to the observed annual temperature. Observed average temperatures ranged between 64.1°F and 66.1°F at the three weather station locations. Parkersburg, WV, had the lowest observed annual temperature at 64.1°F, and Charleston, WV, had the highest annual temperature at 66.1°F. All model spreads for average annual temperature were greater than the mean observed values, indicating that GCMs overestimate annual temperature values in these locations. Only one location, Bluestone Lake, had the model spread fall within the 90% confidence interval, with the model spread ranging from 64.5°F to 64.9°F; the median model hindcast value of 64.7°F fell below the model spread, but the high value for the 90% confidence interval of 64.9°F includes the model spread in the 90% confidence interval. The 90% confidence interval around the observed mean for Bluestone Lake, WV ranges from 63.9°F to 64.9°F, with a mean observed value of 64.4°F. The other two locations, Charleston, WV, and Parkersburg, WV, do not include the model spread within the 90% confidence interval of the mean temperature value. The greatest difference between the model spread and observed average value was in Parkersburg, WV, with a difference of 1.3°F. The observed average temperature in Parkersburg, WV, was 64.1°F (with a 90% confidence interval from 63.8°F to 64.4°F) and a median hindcast value of 65.4°F. Charleston, WV, had slightly closer hindcast projections, with a difference between the mean observed value and the median hindcast value of 0.9°F. The observed temperature value in Charleston was 66.1°F (with a 90% confidence interval from 65.8°F to 66.5°F), while the model hindcast median was 67.0°F. The model hindcasts for average temperature do not appear to flatten temperature across the weather stations as much as the precipitation was flattened across the three weather stations for this region. Average temperatures were generally overestimated by model hindcast projections across the weather station locations, showing a consistent trend across the weather stations for average temperature.

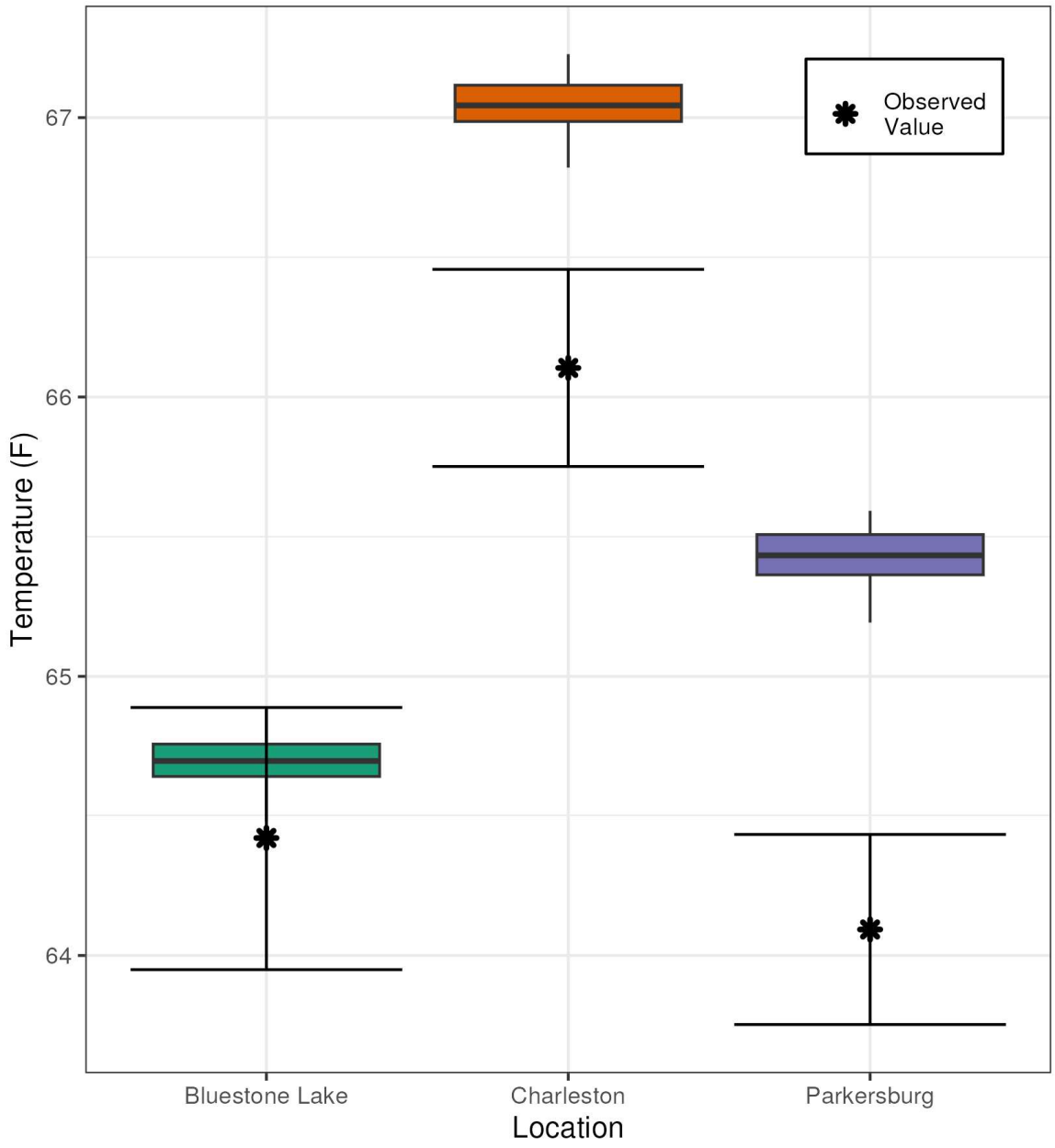

Figure 4.3 Average maximum temperature hindcast model outputs compared to observed data at three selected Appalachian weather stations: Bluestone Lake, WV; Charleston, WV; and Parkersburg, WV

Similar trends were present for the heat wave event comparison as were present for the average maximum temperature. Boxplots were, again, used to compare the observed number of two-day heat wave events (two consecutive days with high temperatures above 90°F) to the model hindcast number of two-day heat wave events (Figure 4.4). Overall, heat wave events were the closest to observed values (with a 90% confidence interval) of all indices compared in this study, with all three observed average values and 90% confidence intervals overlapping with some portion of the model hindcast spread; however, for all three weather station locations, the mean number of observed heat wave events fell below the median number of hindcast heat wave events. Bluestone Lake, WV, had the mean observed heat wave count closest to the median hindcast heat wave count, with the mean number of observed heat wave events at 5.85, and the median number of hindcast heat wave events at 6.59. Bluestone Lake's lower quartile to upper quartile hindcast model spread also fell within the entirety of the 90% confidence interval, with the model Q1 – Q3 range falling from 6.04 – 7.16, and the 90% confidence interval around the mean ranging from 3.86 – 7.84. Parkersburg, WV, had the greatest difference between the observed value and the model hindcast value, with the mean observed value at 8.7 and the median hindcast value at 13.5. Parkersburg did not have any of the 90% confidence interval overlap with the interquartile range of the model hindcast spread. Charleston, WV, also had the observed heat wave value fall below the hindcast median value, with the mean observed heat wave count at 12.3 and the median hindcast value at 15.0. The upper range of the 90% confidence interval for Charleston's observed heat wave count fell just below the median hindcast value, with the highest range of the 90% confidence interval at 14.5. For all three locations, the mean observed number of heat waves fell below the spread of model hindcasts for heat waves, which matches the trends with observed annual maximum temperature; however, the discrepancies are less than the discrepancies with observed average maximum temperature as more of the model spreads falling within the confidence interval.

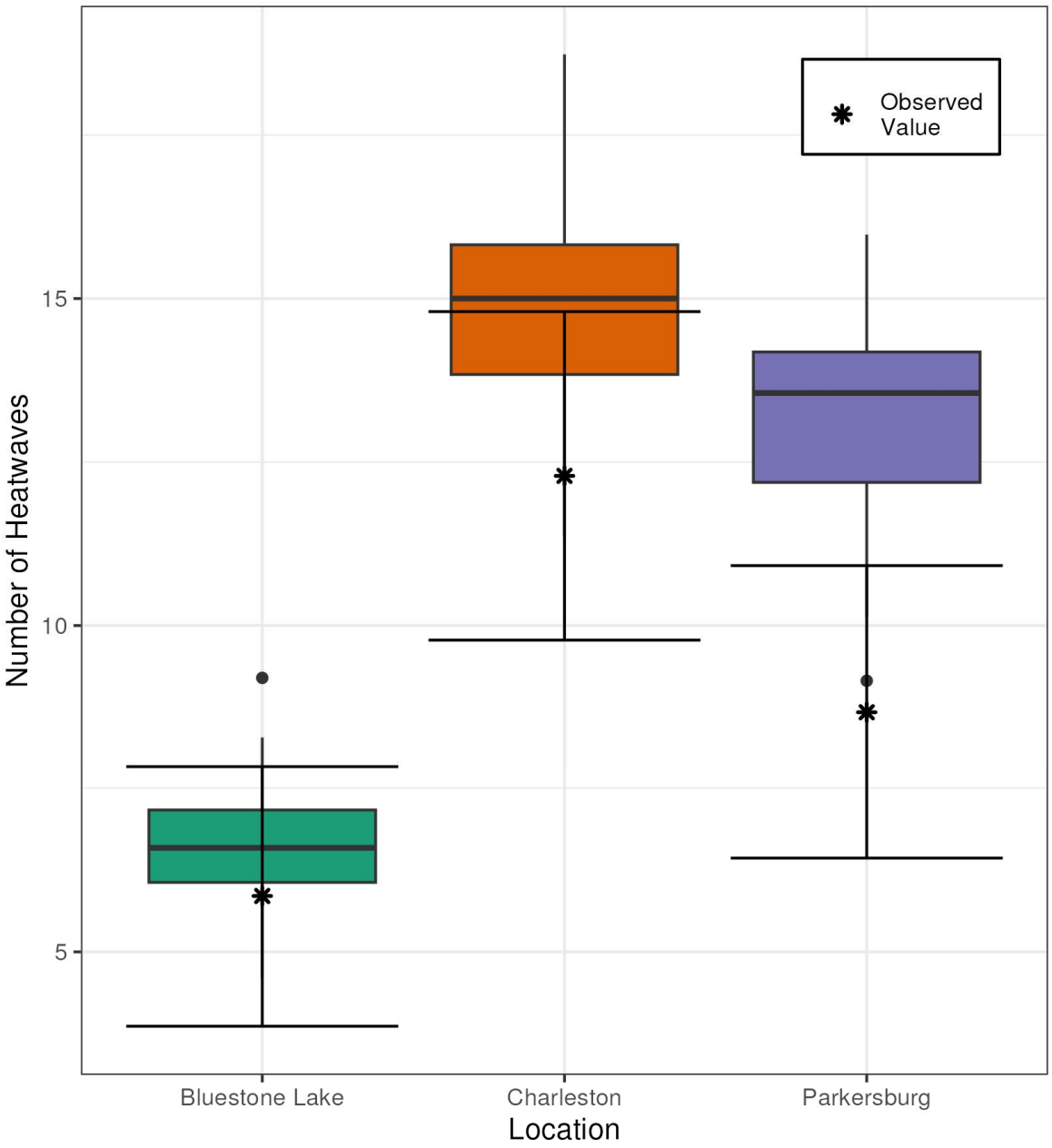

Figure 4.4 Frequency of two-day heat wave events hindcast model outputs compared to observed data at three selected Appalachian weather stations: Bluestone Lake, WV; Charleston, WV; and Parkersburg, WV

4.3 Projected Climate Impact Drivers

4.3.1 Projected Precipitation

To quantify potential annual precipitation scenarios, precipitation was projected in the three primary Appalachian towns in this study: Pulaski, VA; Williamsburg, WV; and Nelsonville, OH (Figure 3.1). For projected precipitation values, boxplots were created to show the spread of potential future precipitation values under two emissions scenarios: a low-emissions scenario (ssp126) and a high-emissions scenario (ssp585). Precipitation is shown as a change from hindcast values to quantify the expected change in precipitation rather than an absolute value. In all three Appalachian towns, total annual precipitation values are expected to increase in the future (Figure 4.5); these changes are greater under the high emissions scenario, with a difference of almost 2 inches between the low and high emissions scenario during the end-of-century timescale (2075 – 2099); however, some minimum values for the model spreads indicate decreased annual precipitation, with precipitation changes dipping below zero, particularly in low emissions scenarios at all locations. For the low emissions scenario on the midcentury timescale (2040 – 2064), all three locations have a relatively consistent increase in precipitation from hindcast values, with a median increase of 2.3 inches in Pulaski, a median increase of 2.2 inches in Williamsburg, and a median increase of 2.1 inches in Nelsonville. The end-of-century low emissions scenario is also similar, with median increases of 2.9 inches, 3.0 inches, and 3.0 inches at the respective locations. As expected, a high emissions scenario has a much greater impact on annual precipitation values. For the midcentury, high-emissions scenario, annual precipitation values are expected to increase by 3.3 inches in Pulaski, VA; 3.3 inches in Williamsburg, WV; and 3 inches in Nelsonville, OH. By the end-of-century timescale, precipitation values are expected to increase by 4.5 inches, 5 inches, and 4.6 inches in the respective locations. It is also worth noting that the spread of models increases under higher emissions scenarios. Given the context with the hindcast annual precipitation values being "flattened" by models across the region, it is unsurprising that precipitation change trends are relatively consistent throughout the three Appalachian towns. Increases in precipitation trends are also unsurprising, given that air temperature and water holding capacity of air are positively correlated; under higher emissions scenarios, air temperature will increase more, thus increasing the water holding capacity of the atmosphere and overall precipitation. Increases in precipitation and river discharge have been observed for the eastern United States, including the Appalachian

region, from 1979 – 2008 (Trenberth, 2011). It is important to note that average precipitation values increase more in midcentury and end-of-century timeframes under greater emissions scenarios. On average, the three positive deviance areas in this study can expect to see approximately a 10% increase in precipitation under the greatest emission scenario by the end of the 21st century.

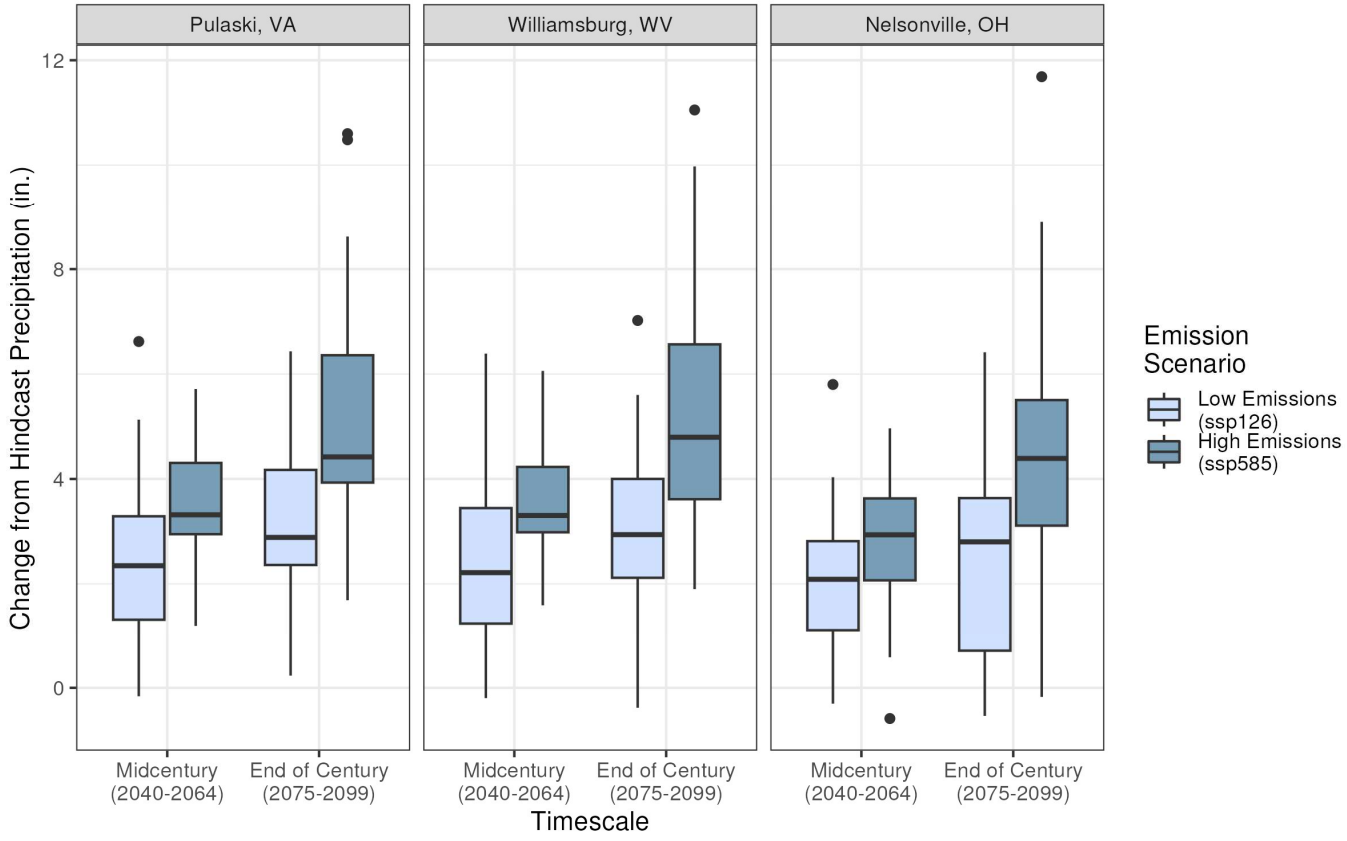

Figure 4.5 Projected change in annual precipitation from model hindcast values under low and high emissions scenarios in Pulaski, VA; Williamsburg, WV; Nelsonville, OH.

Extreme rainfall scenarios, defined as maximum total rainfall over a five-day period, shows the same trends as annual precipitation (Figure 4.6); boxplots are again used to capture the potential increases in five-day precipitation in the midcentury and end-of-century timescales. At all timescales under both emissions scenarios, median five-day precipitation is expected to increase. However, some minimum values for the model spread indicate a decrease in precipitation, with a minimum value for Pulaski's midcentury, low emissions scenario indicating a five-day precipitation decrease of 0.17 inches and Williamsburg's minimum for end-of-

century, low emissions scenario indicating a decrease of 0.25 inches. The model spread also indicates potential high values, with median five-day precipitation values increasing by 0.38 inches in Pulaski, by 0.41 inches in Williamsburg, and 0.50 inches in Nelsonville for the end-of-century high emissions scenario. The greatest expected change at the end-of-century timescale between the low emissions scenario and high emissions scenario is in Nelsonville, OH, with the low emissions scenario indicating an expected change of 0.25 inches and the high emissions scenario indicating an expected change of 0.50 inches, yielding a difference of 0.25 inches. Similar trends are evident in Pulaski, VA, and Williamsburg, WV, however the difference is less. Pulaski expects a 0.05 inch difference in preciptation between the low emission, end-of-century precipitation change of 0.30 inches to the high emission, end-of-century precipitation of 0.35 inches. Williamsburg expects a 0.05 inch difference in preciptation between the low emission, end-of-century precipitation change of 0.31 inches to the high emission, end-of-century precipitation change of 0.37 inches. Changes between 0.25 and 0.5 inches in a 3.0 inch event is between an 8% and 16% increase in five-day precipitation. While precipitation changes of less than an inch may not seem particularly impactful, increases in precipitation can quickly compound and overwhelm water infrastructure, leading to flooding or dam failure. From the precipitation figures (Figures 4.4 & 4.5), it is important to note the impact that emissions scenario has on precipitation values. Annual and extreme precipitation values are expected to increase more under greater emissions scenarios, showing the impact of human activity on future extreme weather.

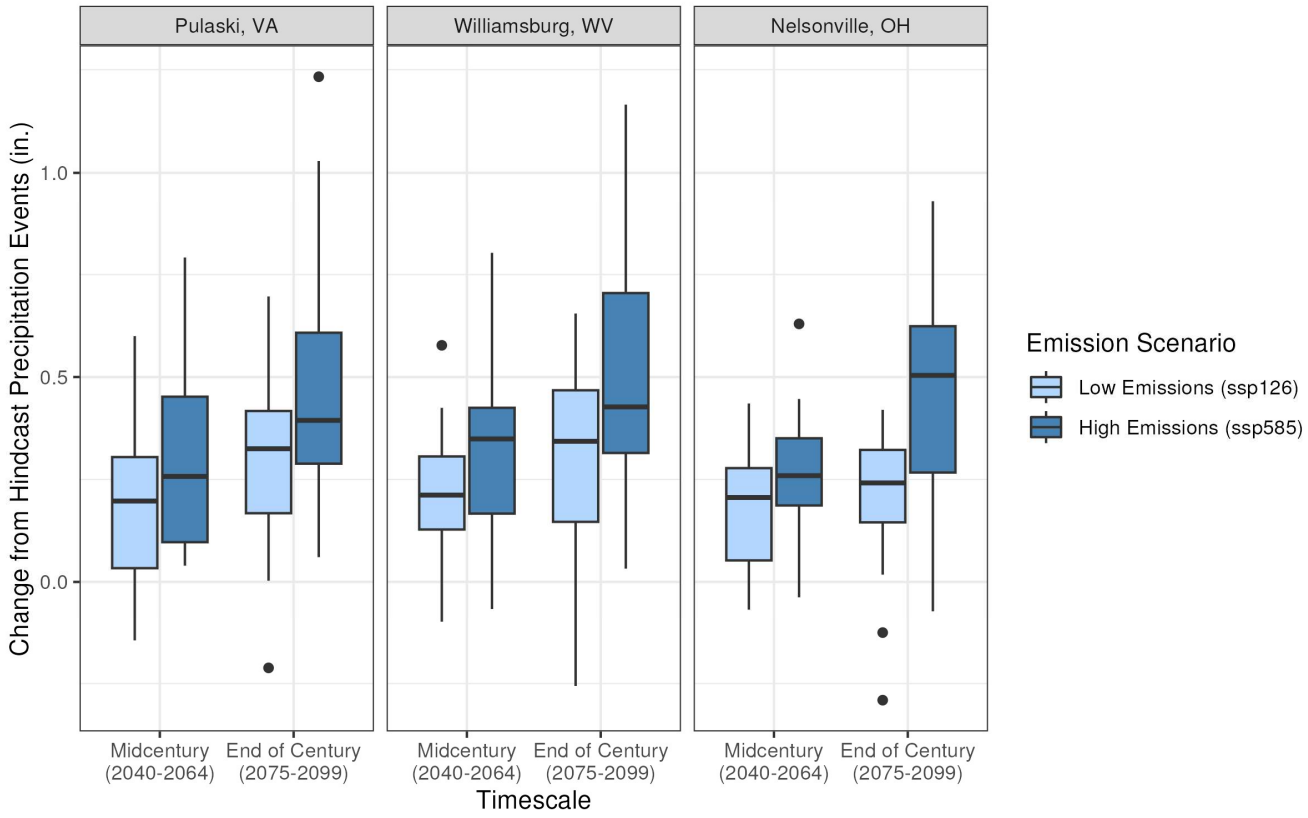

Figure 4.6 Projected change in five-day precipitation from model hindcast values under low and high emissions scenarios

4.3.2 Projected Temperature

In the Appalachian towns of interest, average maximum temperature was also projected under low and high emissions scenarios at midcentury and end-of-century timescales; results are shown in boxplot form to capture the potential spread of models (Figure 4.7). Projected changes in maximum temperatures are expected to increase over time under both emissions scenarios and at both timescales. By midcentury, the median average annual temperature could increase from 2.5°F – 5°F in the Appalachian towns, depending on the emission scenario. Interestingly, emissions scenarios appear to have a large impact on the maximum temperature. Under the low emissions scenario, the change in maximum temperature remains relatively consistent between the midcentury and end-of-century timescale. The three Appalachian towns saw relatively little difference in median maximum temperature change under a low emissions scenario: Pulaski saw a median midcentury change of 3°F and a median end-of-century change of 3.1°F. Williamsburg saw a median midcentury change of 3°F and an identical end-of-century change of 3°F.

Nelsonville actually saw a decrease in median temperature from midcentury to end-of-century, with a median midcentury value of 3.2°F and a median end-of-century value of 3.1°F. Between the midcentury and end-of-century timescales for the low emissions scenario, the range of the model spread increased in all locations. Temperature changes become much more stark under higher emissions scenarios. The midcentury change in average maximum temperature for the high emissions scenario is greater than the low emissions scenario, with temperatures in Pulaski, Williamsburg, and Nelsonville, expected to change by 5.0°F, 5.2°F, and 5.5°F respectively. The end-of-century high emissions scenario has a much greater temperature increase, with median increases in the Appalachian towns increasing by 8.8°F, 9.0°F, and 9.6°F respectively under a high emissions scenario. High projections for end-of-century average maximum temperature could potentially increase by over 12.5°F in Nelsonville, looking at the upper range of the model spread. Pulaski and Williamsburg projections do not indicate changes over 12.5°F, but their upper ranges are relatively close, with maximum potential projections of 12.0°F and 12.2°F respectively. Annual maximum temperature appears to be heavily influenced by emission scenario, with larger changes from hindcast maximum temperature apparent in all three of the Appalachian towns under higher carbon emissions scenarios. By the end of the century under a high emissions scenario, there is expected to be a median increase in maximum temperature of approximately 13%, assuming an average observed maximum temperature of 65°F.

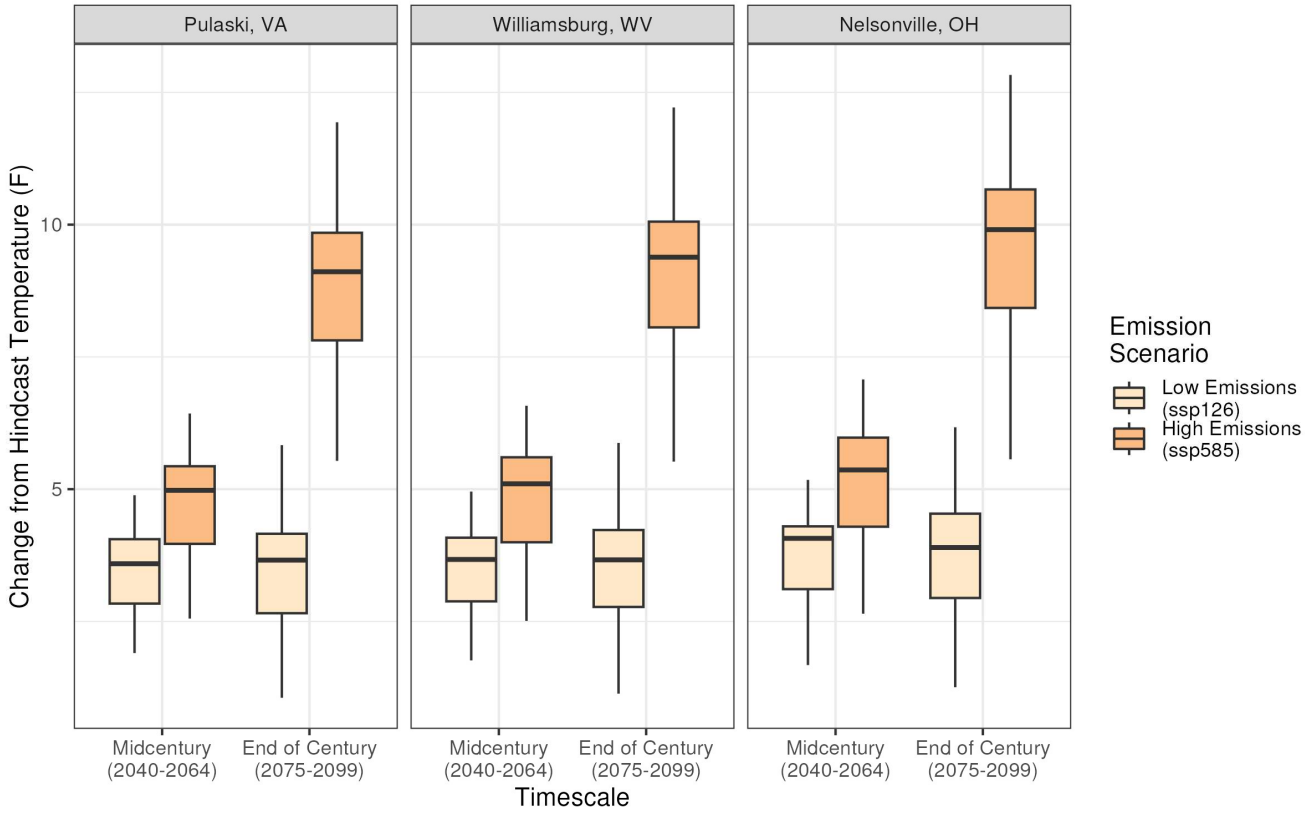

Figure 4.7 Projected change in average annual maximum temperature from model hindcast values under low and high emissions scenarios

Increases in average annual maximum temperature correlate with increases in heat wave events. Heat wave events in this study are classified as two consecutive days above 90°F, and were compared under low and high emissions scenarios across the Appalachian towns (Figure 4.8). Like maximum temperature increases, heat wave events are expected to increase under a low and high emissions scenario; however, there is a difference in number of heat wave events between the low and high emissions scenarios. Across the three Appalachian towns, number of heat wave events in the low emissions scenario have a relatively consistent median number of projected heat wave events. In two of the three Appalachian towns, Pulaski and Williamsburg, the median number of heat wave events decreased from the midcentury timeframe (2040 – 2064) to the end-of-century timeframe (2075 – 2099). Pulaski saw a decrease in heat wave events from 5.8 events to 4.9 events from midcentury to end-of-century, and Williamsburg saw a decrease in heat wave events from 7.8 to 6.8. Nelsonville saw an increase in heat wave events from 11.2 events to 12.2 events. In general, all three towns differed between midcentury and end-of-century

timeframes by about 1 heat wave event under a low emissions scenario, which is a relatively insignificant change compared to changes under higher emissions scenarios. It is worth noting that, like other metrics, the range of projected heat wave events increases from the midcentury to end-of-century timeframe. Under a high emissions scenario, the number of heat wave events increases much more rapidly on the same timescale compared to the low emissions scenario. Overall, Nelsonville had the highest number of heat wave events; in the midcentury scenario, the median number of heat wave events increases by 21.2 events, and increases to a median value of 65.4 heat wave events for the end-of-century timeframe. While not as extreme, these same trends are apparent in Pulaski and Williamsburg. For Pulaski, the increase in heat wave events is 9.1 for the midcentury timeframe and 36.6 for the end-of-century timeframe, and for Williamsburg, the increase is 12.9 and 47.5 respectively. Also of note is the potential extremes of the end-of-century high emissions scenario spread. Pulaski, Williamsburg, and Nelsonville have maximum projected two-day heat wave events (including outliers) of 87.8, 100.3, and 108.0 respectively. Changes of up to 60 more heatwave events from hindcast scenarios with an average of 10 heatwaves in the region is a 600% increase in extreme heat events by the end of the 21st century.

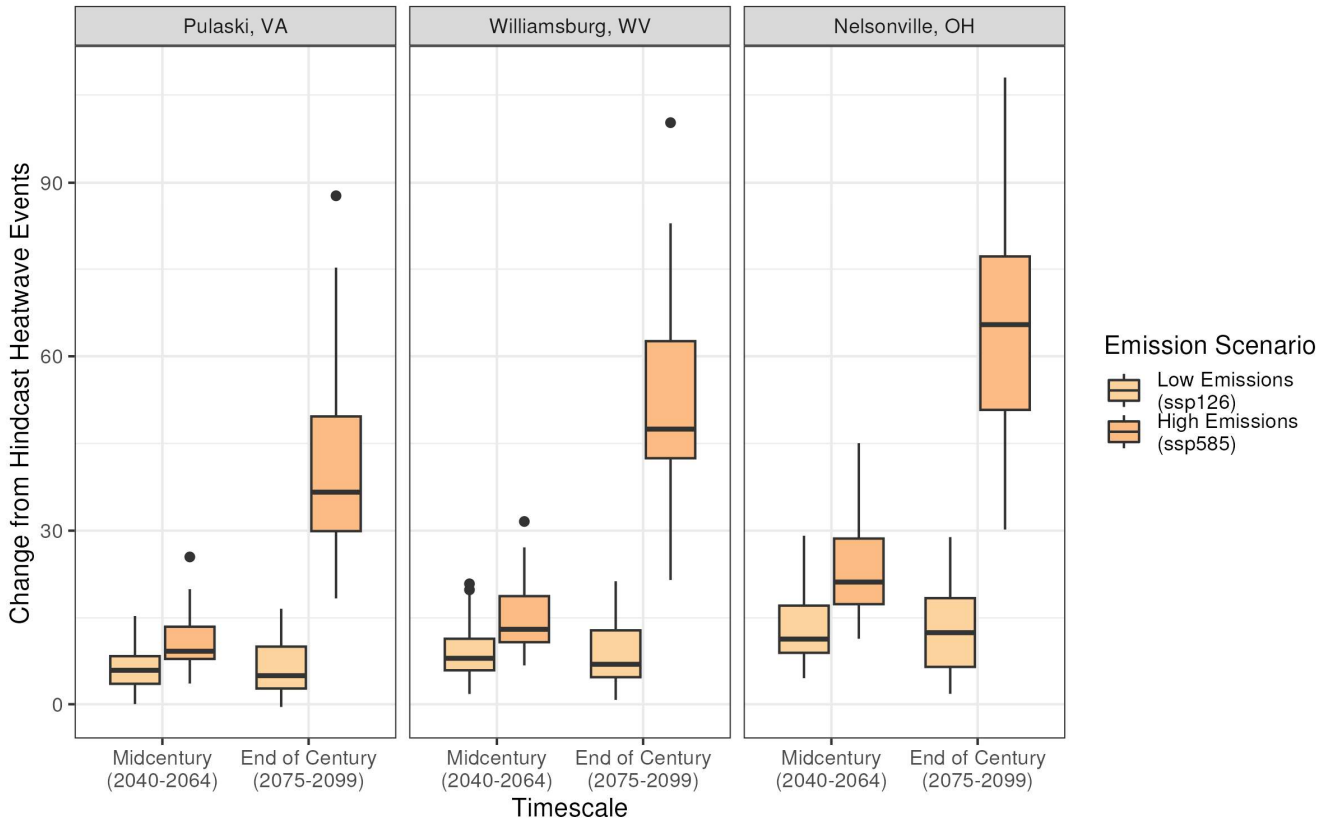

Figure 4.8 Projected change in two-day heat wave events from model hindcast heat wave events under low and high emissions scenarios

5. DISCUSSION

5.1 Hindcast Climate Data Comparison to Observed Records

5.1.1 Precipitation Comparison

Generally, precipitation patterns were captured by the spread of climate models; the Appalachian region generally gets annual precipitation totals between 35 – 60 in./year (NWS, n.d.-b), which was captured by the hindcast models showing between 41 and 43 in./year (Figure 4.1). Climate models are best at capturing observed historic trends, which is present at the weather stations in this study. Hindcast model projections matching observed data does not occur in all locations. For example, some model precipitation projections show increases and decreases in future precipitation values, leading to inconclusive direction about future precipitation patterns (Daron et al., 2021). Precipitation patterns are generally captured for this region by GCM hindcasts, which gives some confidence the models are useful in this area. Models will never be able to completely capture individual events due to limitations in within model characteristics; historical observed data trends being captured by models is indicative of model applicability to a region (Raju & Kumar, 2020). Model hindcasts generally capturing trends in the northeastern United States is consistent with another study comparing CMIP6 models to observed historic data (Agel & Barlow, 2020). The general trends in annual and extreme precipitation captured at the Appalachian weather stations indicate that, to some extent, models can capture long-term average precipitation trends.

Five-day precipitation values for the region were also captured by the GCMs (Figure 4.2). In general, five-day precipitation hindcasts were within 1.5 inches of the observed average five-day precipitation event, showing hindcast projection that are generally consistent with historic observations. However, all GCMs in this study underestimated extreme rainfall events at the three weather stations in the Appalachian region. Discrepancies between GCMs and observed local weather data when investigating extreme precipitation are common, as rainfall events are particularly challenging to simulate in a GCM (Agel & Barlow, 2020; J. Li et al., 2020; Mishra et al., 2014). This is particularly of interest when observing season-specific events, such as summer precipitation and orographic thunderstorms (Raghavan et al., 2018). Extreme precipitation has also been documented to be underestimated by models over time, as observed extreme precipitation has been increasing at a faster rate than climate models have previously simulated (Asadieh & Krakauer, 2015). In Appalachia specifically, the primary weather systems

driving large rainfall accumulations are orographic convective systems, which could contribute to faster rates of precipitation changes. These systems generally cause large precipitation accumulations in rain shadows and drier regions between mountains. Due to these complex orographic systems, Appalachian precipitation patterns are heterogeneous across the region, making local precipitation difficult to capture, especially in a global-scale model system (Smith et al., 2011).

Complex hydrology and weather patterns in Appalachia impact the relationship between model hindcast values and observed data. Overall, the models seem to "flatten" precipitation across the region, showing values closer to average precipitation than the observed variations across the region (Figure 4.1). This leads to overestimation and underestimation of observed precipitation values at these weather stations. Other studies that have shown both overestimations and underestimation in annual precipitation metrics using previous iterations of the CMIP ensemble GCMs (CMIP3 and CMIP5), including in East Asia and the northeast region of the United States, including Appalachia (Agel & Barlow, 2020; Raghavan et al., 2018). In a previous study analyzing 16 models in the CMIP6 ensemble, projections between 1950 – 2014 over the northeastern United States (including the Appalachian region), different models simulated seasonality, spatial distribution, and precipitation intensity with variations in accuracy compared to observed data (Agel & Barlow, 2020). Some models simulated average precipitation well, but did not simulate extreme precipitation events sufficiently; other models did the opposite, simulating extreme events well but insufficiently capturing average values (Agel & Barlow, 2020). Additionally, some models exhibited overestimations or underestimations of observed values depending on the season (Agel & Barlow, 2020). Observations of GCMs having varied accuracy in precipitation hindcasting, as well as individual models having strengths and weaknesses with different CIDs, are consistent with the overestimation and underestimation of observed models between hindcast models from 1970 – 2014 in this study.

5.1.2 Temperature Comparison

Appalachian average temperature trends were generally captured by the hindcast model spread. Average temperature in the region ranges between 62°F – 67°F (Kutta & Hubbart, 2019), which is captured by the hindcast spread medians ranging between 64°F – 67°F. This shows that Appalachian average temperature trends are captured by the CMIP6 hindcast projections,

indicating with some confidence that the climate models can simulate temperature trends in the region. Two-day heat wave events, defined as two consecutive days above 90°F, were also overestimated by the models, though the deviations were lower (Figure 4.4). While the average temperature of the three observed locations were all less than the model estimations, the 90% confidence interval intersected with the spread of models, unlike with the average annual temperature.

In terms of biases, average annual temperatures predicted by CMIP6 were overestimated when compared to GHCN observed data at the three weather stations (Figure 4.3). Only hindcast data from one location, Bluestone Lake, WV, had models fall within the 90% confidence interval of the observed averages. The other two locations, Charleston, WV, and Parkersburg, WV, saw model values above the average temperature value and 90% confidence intervals. One potential cause of this consistent overestimation of the models could be the weather stations' location near bodies of water. The Bluestone Lake, WV, and Parkersburg, WV, weather stations also have stream gauges at these locations and are directly adjacent to water; the cooling effect of the nearby bodies of water could lead to cooler temperatures compared to inland locations. Studies specifically about cooling effects of water have documented this effect, which could be occurring in hindcast comparisons to observed data (Gupta et al., 2019). Some climate models may have urban biases as well (Scafetta, 2021), which could impact model hindcasts. Additionally, the Bluestone Lake weather station was located at an elevation of 424 feet; this is nearly 200 feet above the Charleston and Parkersburg weather stations at 278 feet and 245 feet respectively. In other studies looking at the relationship between GCMs and elevation, there are limitations in models accurately capturing climate aspects in areas of complex elevations or steep elevations changes (Palazzi et al., 2019). GCMs generally use linear relationships between elevation and climatic changes, but this relationship is not entirely accurate based on observation (Palazzi et al., 2019). This could also be part of the discrepancy between the observed data and hindcast projections as weather stations in Appalachia can be in areas with steep topography change, particularly those weather stations that double as stream gages.

5.1.3 Importance of Hindcast Comparison to Observed Data

In context with comparisons to observed data, the CMIP6 models capture the general observed climatic trends. With annual precipitation and temperature, the spread of hindcast models generally coincides with average observed precipitation and temperature. General trends

are captured at the three weather stations in this region, which provides some confidence that models capture trends in the region, including projected scenarios.

While trends are captured in the region, there are some local discrepancies in the region due to inherent limitations of modeling regional climate with global climate models. Temperature and precipitation hindcast data saw variation in simulated averages values and underestimation of extreme values. This can be attributed to coarse, global climate models typically not capturing unique local weather patterns, so some variation between hindcast projections and observed weather is expected (Gates et al., 1995). Variability in precipitation specifically is to be expected at the Appalachian weather stations. GCMs generally distort orographic precipitation specifically, as orographic precipitation is driven by elevation change and local climatic trends; elevation change and local weather patterns are challenging to model, which is a general limitation of GCMs (Gates et al., 1995). As orographic weather has a large influence in the Appalachian region, some discrepancy in precipitation is expected.

Land cover has a large impact on hydrology. Appalachia, as a geographically diverse region, has many land-use and land-cover changes over short areas, which may not be captured accurately in GCMs. The combination of flash-flooding in Appalachia and discrepancies in accuracy of model hindcasts compared to observed values requires care if models are used for decision making. Choosing to use ensemble model projections without considering variability could lead to insufficient preparations in a geographically diverse region like the Appalachian region, especially regarding extreme precipitation.

It is important to note that climate models operate under the assumption of stationarity. Stationarity assumptions in climate models are typically a fundamental assumption in climate models (Chen et al., 2015). Additionally, there are other factors that impact the outcome of weather, and those factors may not change linearly. Compounding variables may also impact changes in climate that cannot be predicted. It was also assumed that indices stayed consistent over the time periods of analysis. In reality, climatic changes have been observed over time (Rummukainen, 2012), and this analysis does not capture potential changes within the periods of analysis. However, even with model limitations, the general agreement to observed values and capturing of general trends indicates, with some confidence, that GCMs are useful and applicable to this region of study.

5.2 Projected Climate Data

5.2.1 Projected Precipitation

Increases in annual and extreme precipitation were projected for the Appalachian towns of interest across all timescales and emissions scenarios; greater changes were observed particularly under more intense emissions scenarios. This is consistent with trends expected from physical climate systems, as well as other studies investigating projected precipitation values from GCMs (Fernandez & Zegre, 2019; Kutta & Hubbart, 2019; Ning & Bradley, 2016; Shiru et al., 2022; Trenberth, 2011). Increases in Appalachian precipitation specifically are consistent with projections from a similar study using the previous iteration of the CMIP5 data (Fernandez & Zegre, 2019). In a study investigating projected extreme precipitation indices using the CMIP6 ensemble, maximum five-day precipitation events are expected to increase across the United States, particularly in the northeast and southeast regions, of which Appalachia is included (Akinsanola et al., 2020). This is consistent with findings in this study showing increases in maximum five-day precipitation for the Appalachian towns (Figure 4.6), particularly under higher emissions scenarios. These trends also are consistent with historical observations, as observed daily precipitation trends increased between 1980 – 2018 in the northeast and southeast United States (Dollan et al., 2022).

It is important to recognize that while a five-day timescale is useful in examining long-term trends in extreme precipitation events, significant natural disasters are associated with short-duration events that stress existing infrastructure. In the Appalachian region, where location of towns can heavily impact the chance of flooding due to location in valleys and proximity to waterways, even small amounts of precipitation change could impact the severity of the flooding in the region (Kruse-Daniels, 2024; Morrone, 2020). For example, in Buffalo Creek, WV, the NOAA disaster investigation report estimates that up to 5.6 inches of rain fell in about 18 hours on February 26, 1972, leading to the eventual dam failure that caused the historic flooding (Baker et al., 1972). The eastern Kentucky floods of 2022 saw similar precipitation patterns with some areas receiving up to 8 inches of rain in 24 hours (NWS, n.d.-b). Existing predictions suggest flooding may become more likely due to the combination of aging infrastructure and increasing precipitation, as stormwater infrastructure typically gets overwhelmed by short, high-intensity precipitation events. While five-day precipitation is a

generally recognized indicator in global climate change discussions, the precipitation trends in Appalachia may be better represented by other indices for extreme precipitation events.

When using precipitation projections for planning purposes, it is important to consider insights gained from the hindcast comparison. In the three Appalachian towns, five-day precipitation values were consistently underestimated by the model spread. Appalachian flooding is also heavily influenced by land-use changes associated with extractive resource economies, especially mountaintop removal. In experimental watersheds in Ohio, the NRCS Curve Number on mined lands increases between 7 and 20 between the start and end of mining procedures (Eshleman & McCormick, 2009). However, the NRCS Curve Number criteria do not consider reclaimed lands, which can lead to an underestimation of the curve number and overall underestimation of runoff. This could be partly due to the complex hydrological climate of the Appalachian region and further impacted by land cover changes caused by extractive economies (Kutta & Hubbart, 2019). Mountaintop removal and fill mining practices change hydrology, from soil water holding capacity to runoff rates (Day & Chen, 2024; A. Miller & Zégre, 2014). Mountaintop removal has even resulted in death from extreme flooding (Spadaro, 2005). Mountaintop removal and other quick landcover changes indicate the complex relationship between precipitation and flooding in Appalachia, which is important to consider in flood mitigation efforts; this indicates that more information than precipitation values may be necessary for sufficient planning.

If five-day precipitation projections from GCMs are used for planning in these regions, they must account for local land use and identified projection bias to avoid underestimating future five-day precipitation values, especially if absolute values from GCMs are fed into other hydrologic or flood risk models. Ideally, in planning scenarios future values should be communicated as a change from hindcast model values rather than an absolute projected value in effort to mitigate some local biases when comparing hindcast projections to observed data.

5.2.2 Projected Temperature

In all three Appalachian towns, average temperature and number of heat wave events (two consecutive days above 90°F) are expected to increase; the increase is expected to be greater at the end of the 21st century and under higher emissions scenarios. As with the precipitation projections, this is consistent with other studies that used previous CMIP iterations (CMIP3 and CMIP5) to investigate extreme heat changes in the United States. These studies

reported increases in average annual temperature and extreme heat/heat waves, which were linked to increasing estimates of number of deaths from heat-related illness (Peng et al., 2011; Raymond et al., 2022). Increasing average and extreme heat shows a consistent trend across the Appalachian towns; magnitudes of average annual temperature are expected to increase between 3° – 10°F depending on emission scenario and timescale (Figure 4.7).

The projected heat wave chart demonstrates the contrasts between emissions scenarios (Figure 4.8). The average number of observed heat waves in the study Appalachian towns ranges from 5.8 two-day heat waves in Bluestone Lake, WV to 12.3 two-day heat waves in Charleston, WV. Areas around these towns could see a total number of heat wave events reach a magnitude upwards of 80 two-day heat waves. Information between emissions scenarios, particularly related to heat, could be used to advocate for emission reduction policies in addition to using information for resiliency planning.

Although the baseline temperatures in this region are not extreme, seemingly small changes in heat can have a large impact on human health, particularly in vulnerable populations (i.e. elderly, children, people with preexisting health conditions, etc.). For example, during the 2003 heat waves in Europe, temperatures were 2°C – 3°C (3.6°F – 5.4°F) hotter than average temperatures; this magnitude of change is possible in Appalachia, especially under higher emissions scenarios, which could contribute to heat-related illness (Wolf & McGregor, 2013). While there are additional factors contributing to heat-related illness in urban settings, such as the urban heat island effect and hotter nighttime temperatures (Heaviside et al., 2017), small increases in temperature can also have detrimental effects in rural areas. Due to limitations in healthcare access, the relative risk of heat exposure in rural areas may be equal or greater than the relative risk of heat exposure in urban areas (Y. Li et al., 2017). Long-term exposure to heat increases the likelihood of heat-related morbidity and mortality. Long-term heat exposure is expected to increase with increased average temperatures and increased heat events (Shindell et al., 2020).

Physical impacts of heat begin to appear with small changes in temperature (Wolf & McGregor, 2013). Physical impacts of heat on the human body include cardiovascular and respiratory disease, dehydration, and thermoregulatory issues. On top of interactions with physiological systems, there are additional challenges that can compound heat-related illness. For example, infants have less thermoregulatory capacity than adults, sweating efficacy is

reduced over age 65, and antidepressants are less effective when the body is under heat stress. In an area with an aging population, limited access to healthcare, and less resources, understanding and preparing for increased heat exposure is important to mitigate negative health outcomes (Ebi, Capon, et al., 2021). Additionally, heat strain is exacerbated by opioids and narcotics, which are epidemic in Appalachia (Ebi, Capon, et al., 2021; Morrone, 2020). In addition to heat physically impacting the body, fan-based cooling becomes less effective. A study investigating productivity under higher temperatures with and without fans shows that once temperatures reach above 3°C (5.4°F) from the average ambient temperature, fans become less effective (He et al., 2019). With changes in Appalachia reaching greater than 5°F under a high emissions scenario, fan efficacy should be considered regarding heat-related illness, especially in areas where air conditioning infrastructure is limited.

Again, it is important to consider the context of temperature predictions in the Appalachian towns. For annual and extreme scenarios, models consistently overestimated temperature values (Figure 4.3 and Figure 4.4). In this instance, planning based on models with overestimated values may provide a margin of error for extreme events, though it is worth noting the uncertainty underlying all model projections.

5.3 Applicability to Positive Deviance Areas

Overall, models appear to capture observed trends and reasonable projected climatic scenarios at the weather stations and positive deviants in Central Appalachia. Models capturing trends does not happen everywhere, so general trends being captured by the GCMs in this region indicates that models could be useful for future projections in the region. Friends of Peak Creek in Pulaski, VA, and the Williamsburg Area Response Team in Williamsburg, WV, (Table 3.1) are already interested and preparing resilience strategies around precipitation projections. The information generated in this study could be useful for planning purposes, especially related to extreme event response. In regards to extreme heat, currently none of the organizations of interest in this study are implementing resilience efforts to address heat. However, this study found increasing temperature trends in the Central Appalachian region, which is consistent with trends in the United States, including from climate models (Peng et al., 2011; Raghavan et al., 2018; Raymond et al., 2022). During listening sessions, heat was mentioned as an area of concern regarding climate-related planning. Increases in heat, particularly information about extreme scenarios, could also be useful to these NGOs for planning purposes.

6. CONCLUSIONS

The three positive deviance towns, Pulaski, VA; Williamsburg, WV; and Nelsonville, OH, can expect to see increases in precipitation and temperature during the 21st century. Changes are seen across both timescales (midcentury, end-of-century), and under low and high emissions scenarios. Changes in both CIDs are evident in both annual and extreme indices. All CIDs experience the largest increase under a projected high emissions scenario at the end of the century.

Annual precipitation in the positive deviance towns is projected to increase from 2 to 5 inches, which is an increase from observed conditions of 5% – 12% by the end of the 21st century. Five-day precipitation is expected to increase between 0.25 and 0.5 inches, which is approximately a 14% increase from the greatest observed five-day precipitation event (3.6 inches) at the weather stations in this study. Average temperatures in the Appalachian region are also expected to increase, with temperatures increasing 3°F – 10°F by the end of the 21st century depending on emissions scenario. Heatwaves are also expected to increase by 30 and 60 heat events per year by the end of the 21st century under the highest emissions scenario; this represents a 300% to 600% increase compared to observed values of 10 heatwaves per year. Precipitation and temperature findings are consistent with other studies across the globe, including studies focusing specifically in Appalachia.

Increases in the precipitation and temperature CIDs will likely impact public health. Precipitation changes are likely to cause more flooding in the region, particularly given the topology and location of towns. Hotter and more prolonged heat events are more likely to increase instances of heat-related illness, potentially burdening already strained public health departments. Communicating this information to public health departments and local organizations can serve as an initial step in helping prepare for the public-health-related impacts of extreme weather and climate change.

Projected data shows the impact that emissions scenarios have on climate. The differences between emissions scenarios indicate the importance of using multiple emissions scenarios and a spread of climate models to capture uncertainties inherent in projecting future climate, including those stemming from emissions decisions. Emissions scenarios have a far greater impact at the end-of-century timescale (2075 – 2099) compared to the midcentury timescale (2040 – 2064). Long-term planning should include conditions under different

emissions scenarios to account for various impacts of current and future greenhouse gas emissions policies.

Hindcast simulations from climate model ensembles can be compared to observed weather data to assess potential biases or limitations in GCM capabilities within the region. Due to the coarse resolution of the NASA GCMs, a single raster cell can include a wide range of geographic and topographic features (Figure 5.1). Comparing hindcast model outputs to observed weather conditions is important to understanding if potential future climate scenarios could be overestimated or underestimated. In comparison to observed values, it is also important to consider the geographic area surrounding weather stations. In the comparison of hindcast models to observed data, mean observed temperatures fell consistently below the model hindcast spread. Across the three weather stations, the observed mean values were between 0.65°F and 1.3°F below median hindcast projections In this study, two of the three weather stations were located on or near bodies of water, which could have caused a local cooling effect, thus skewing the average air temperature low. Environmental conditions (i.e. shade, water proximity, urban heat islands) should be noted when selecting or analyzing data, and any environmental conditions that could affect observed data, particularly air temperature, should be considered.

7. LIMITATIONS AND FUTURE WORK

This study aimed to understand the needs of representative communities in Central Appalachia regarding extreme weather events and provide information and resources about potential future climate scenarios. Outputs from NASA's NEX-GDDP CMIP6 ensemble models were used to examine temperature and precipitation values in three towns in the Appalachian region. While data and information were created to support extension materials, this study did not look at the efficacy of these materials. Future studies must investigate the aid these extension materials provide, including areas of information that are lacking. In a study investigating the efficacy of decision support tools related to climate change, many support tools include detailed climate information, but lack context regarding specific decisions and the role climate information plays in the decision-making process (Jahan et al., 2023). This work focused on generating climate information for the region, but does not include information about decisions this summary could prompt or support. Additionally, matching decision-support tools to end user needs is essential for creating tools that will be used by communities (Palutikof et al., 2019). While needs of involved communities were considered by selecting potential CIDs of interest, the method of delivery was not considered in this study. Future work must be done to understand the end-user experience with this information, including most-effective method of delivery (i.e. interactive website, extension bulletin, training, etc.) by including communities in the information-planning stages.

More research into extreme precipitation rainfall indicators should be done to determine which indices are most applicable to the Appalachian region. Historically, floods in the region have been caused by short, intense storms, and heavy precipitation in the region is increasing with the changing climate (Ebi, Vanos, et al., 2021; Romanello et al., 2022). In addition to precipitation increasing across the globe, the Central Appalachian region specifically has also seen some of the largest amounts of rainfall in 6-hour periods (Smith et al., 2011). Since the Appalachian region is primarily driven by orographic thunderstorms—thunderstorms that are produced by air being driven upwards by mountainous terrain—short, intense thunderstorms are the typical catalyst for catastrophic floods in the region (Smith et al., 2011). As such, maximum five-day precipitation may not be the best indicator for intense precipitation events that are likely to cause flooding in the Appalachian region. More research should be done to investigate the relationship between precipitation and flooding events in Appalachia to determine the most-

suitable precipitation metrics. For example, Appalachia's wettest months are typically the summer months, so looking at heavy precipitation specifically in the summer could be a better indicator for precipitation driven specifically by orographic thunderstorms (Akinsanola et al., 2020; Schaller et al., 2011). Other potential indicators that could better represent intense rain when analyzing daily climate data include maximum consecutive wet days, and heavy precipitation days as described by R10 (daily precipitation > 10mm), R20 (daily precipitation > 20mm), and R50 (daily precipitation > 50mm), among others. More extreme precipitation indices can be found in Akinsanola et al. (2020).

Future research should investigate other extreme precipitation indicators throughout the Appalachian region to determine how well these indices correlate to flooding incidents, and if they represent observed conditions well throughout the region. Future studies should also consult decision-makers in the Appalachian region during index selection to determine which metrics would be most useful for planning and decision-making, including direct suggestions for how this climate information should be considered. Appalachian flood events are primarily caused by flash-flooding events. Flash flooding events are particularly dangerous for small communities impacted by orographic thunderstorm events (Perks et al., 2016; Smith et al., 2011). The combination of orographic effects from the nearby mountains, flash-floods, communities located in valleys, and proximity to streams with high flood potential pose significant risks for Appalachian communities. Flash-flooding is particularly difficult to model; since flash-flooding relies on land cover in addition to precipitation. Modeling only precipitation without land cover will not yield a direct relationship to how an area like Appalachia floods (Schumacher, 2017). Modeling for flash-flooding often yields unreliable results (Hapuarachchi et al., 2011). In addition to flash-flooding itself being challenging to model, challenges with modeling the Appalachian region due to diverse topology, hydrology, and climate compound to make flooding in the region even more difficult to understand. Future work must be done to understand flash-flooding and to create more accurate flash-flood models specifically in the Appalachian region. This work should be combined with creating better extreme precipitation indicators and using location-based and time-based downscaling in efforts to create the best possible models for understanding future hydrologic conditions in the Appalachian region.

Analysis of climate model data does not come without limitations; to perform the analysis using the publicly available code developed for this project, a working knowledge of

spatial analysis and R is required. Computing power is also required: this analysis was performed on Virginia Tech's Advanced Research Computing system in parallel using 15 – 25 cores depending on analysis type. Even with these computing resources, analysis took a significant amount of time (approximately 15 minutes per time period and emissions scenario). Computing resources may be inaccessible to certain areas due to financial, physical device, or broadband internet limitations. Some high-performance computing machines are available through universities, and organizations in need of computing can reach out to access necessary computing requirements. It is important to consider the spatial resolution of CMIP6 GCMs used in this analysis . The coarse resolution of the CMIP6 GCMs (without spatial downscaling) significantly limits location-specific information and loses fine detail over the complex topography of the Appalachian region. The approximately 16 mile x 16 mile resolution of the CMIP6 GCMs in the Appalachian region covers a diverse land-cover areas in a single pixel, which simplifies climatic changes that may occur on a local scale (Figure 7.1). GCMs of this resolution may also fail to capture elevation changes or compounding variables in the Appalachian region that cause flooding.

Figure 7.1 Raster grid cells from the ACCESS-CM2 GCM overlayed on the Appalachian towns. The resolution of the ACCESS-CM2 model is 1.875° x 1.25°, which translates to approximately 17 miles x 13.5 miles in the Appalachian region.

Beyond Appalachia, the data and code utilized in this analysis could be useful to communities elsewhere. Using publicly available data and open-source software for analysis would allow agencies to generate projected scenario summaries at no cost; the barriers for analysis would lie in staff availability, computing power, and computing knowledge. The R scripts used for data download and analysis can be found in the public GitHub repository linked

in the code and data availability statement (see section 8). With public health departments and local organizations potentially interested in accessing these projections, including updated projections as new model iterations are published, free, publicly available, climate analysis resources could be a powerful tool in building climate resilience at a local scale.

8. CODE & DATA AVAILABILITY STATEMENT

Data and code can be accessed from the public GitHub repository for this project at https://github.com/nalarsson/AppalachianHealthSupportCIDs. For additional information or questions, contact nlarsson@vt.edu.

Publicly available datasets were analyzed in this study. This data can be found at: 35 CMIP6 models from Earth System Grid Federation (https://aims2.llnl.gov/search/cmip6/, downloads completed November, 2023); GHCN Daily (https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily**,** downloaded September 27 & 28, 2023)

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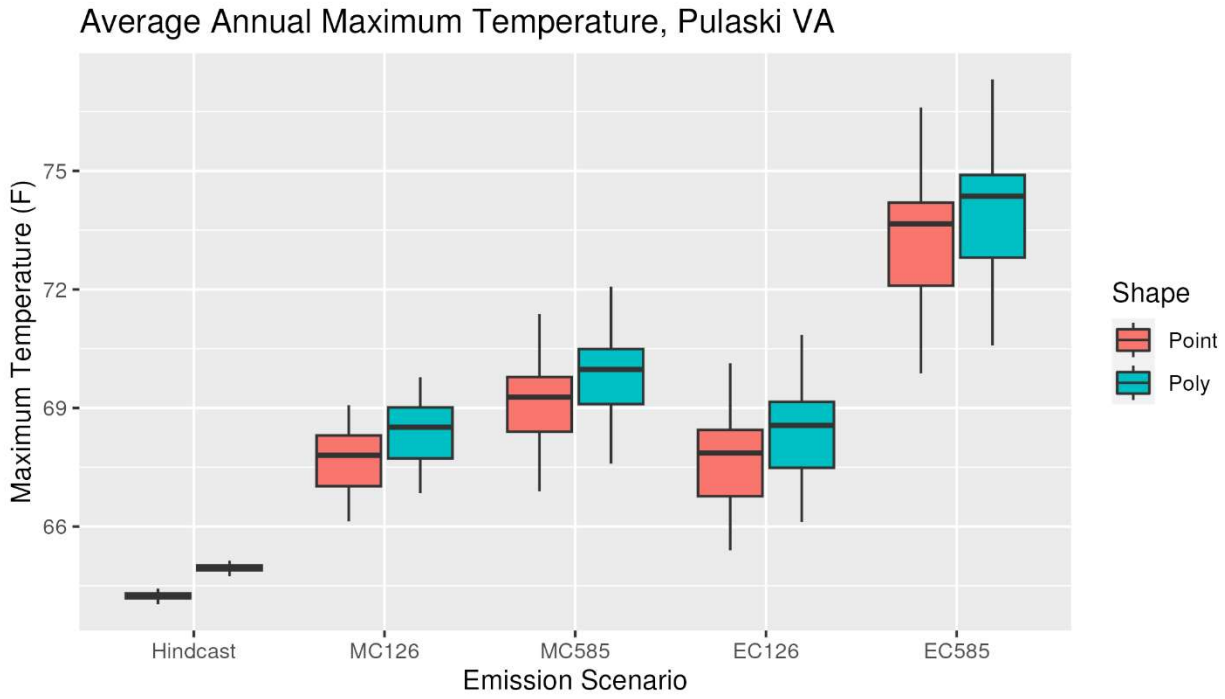
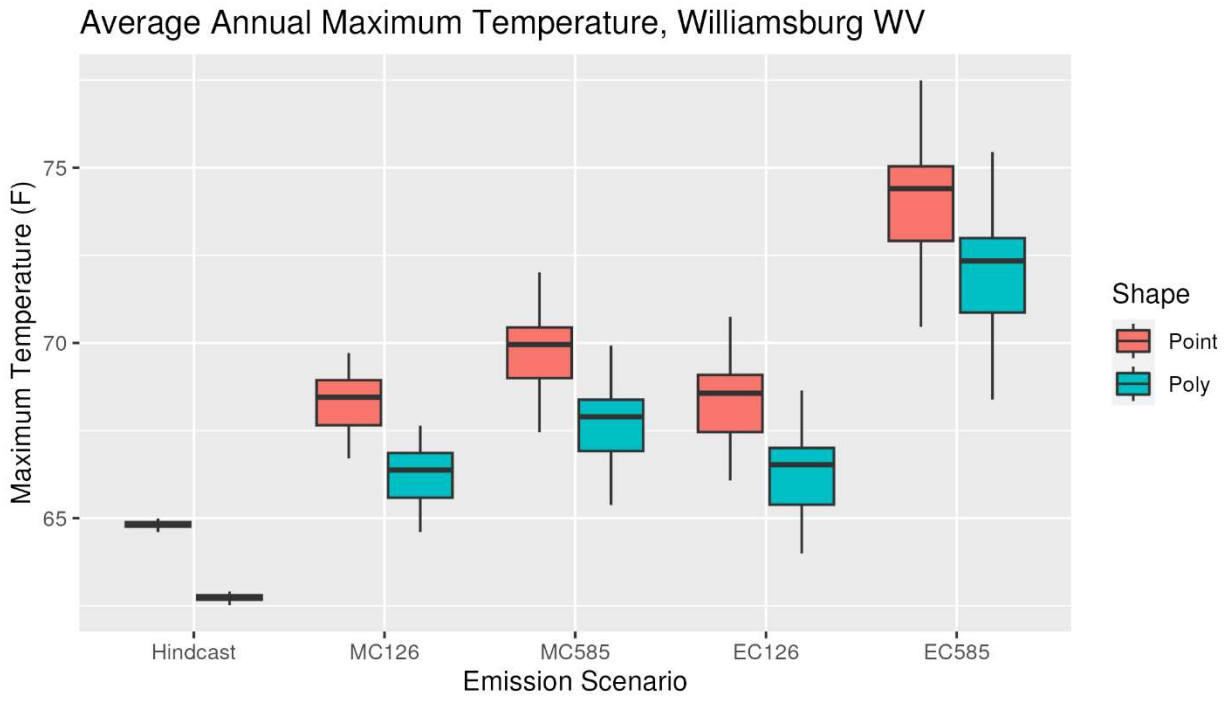
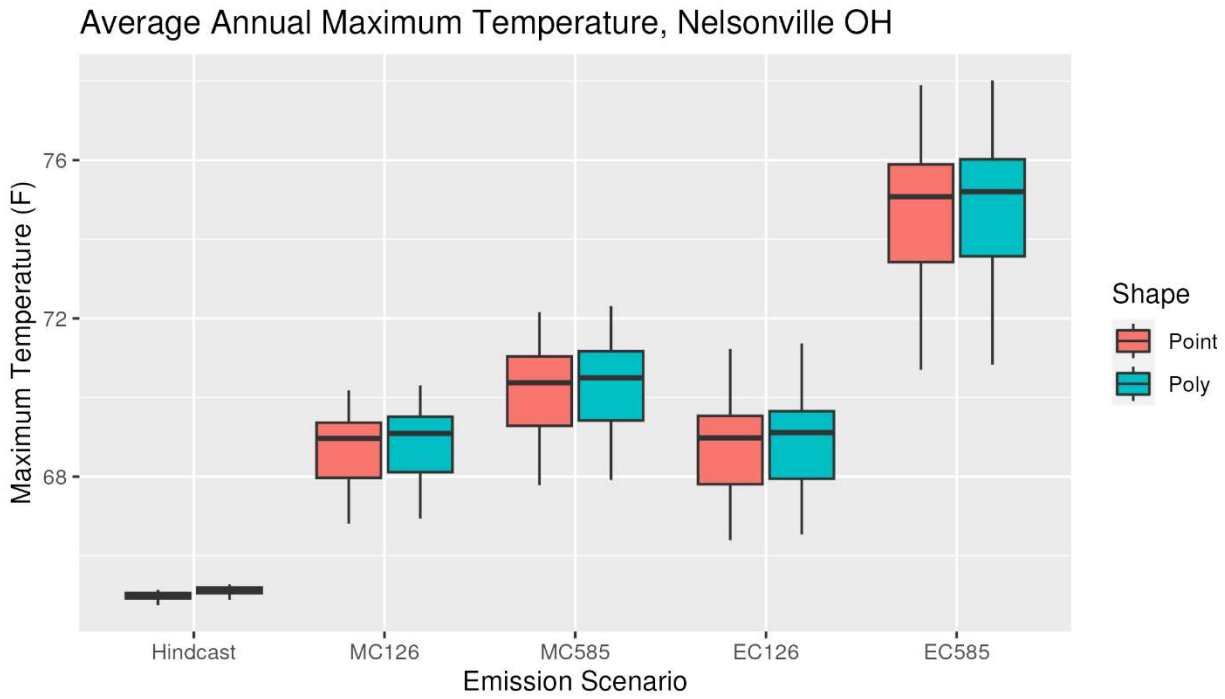
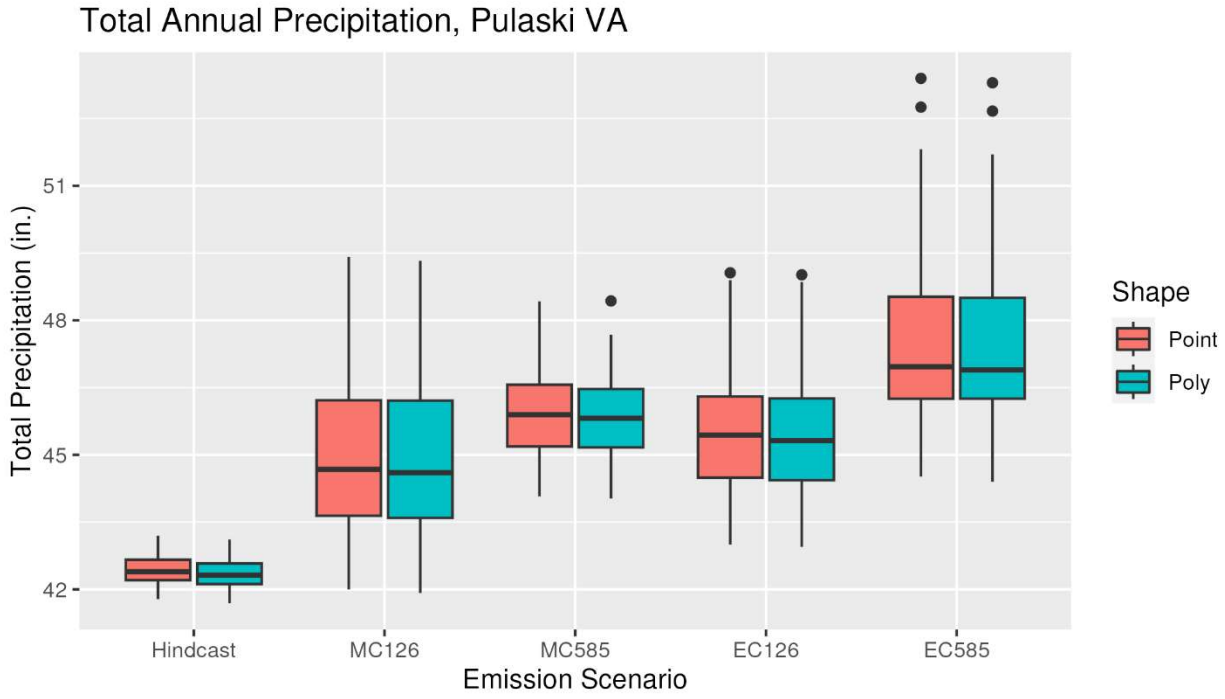
Appendix A. Point Extraction versus Polygon Extraction Results

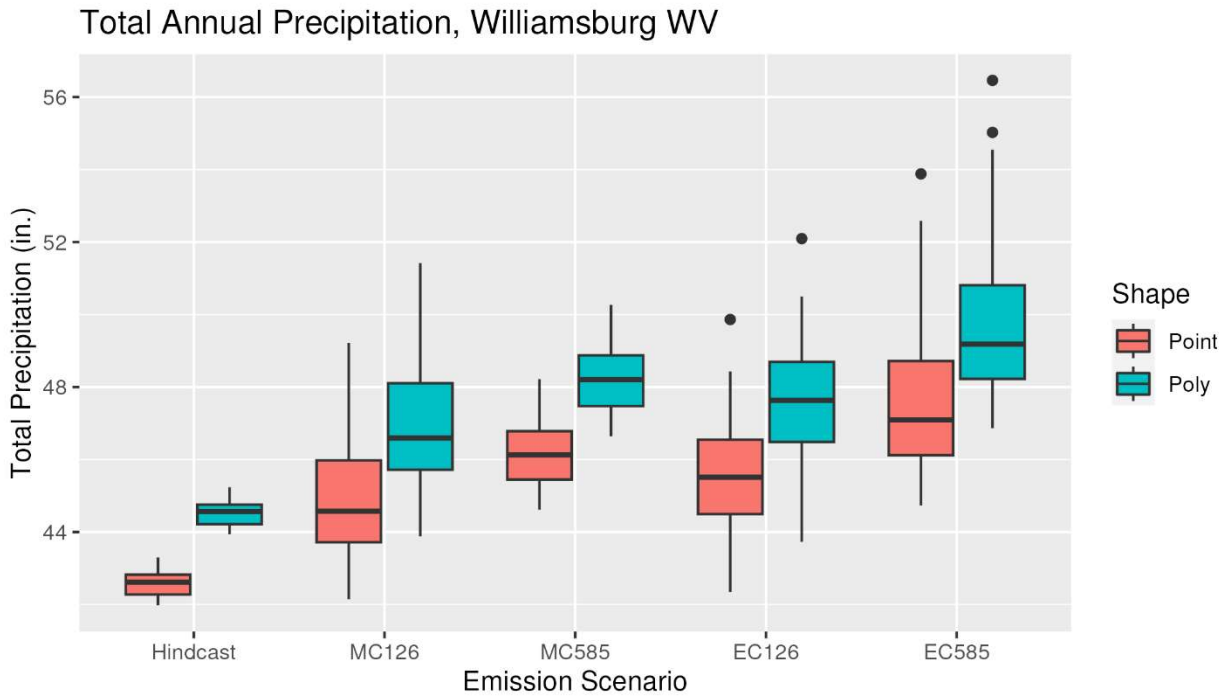
Point extraction versus polygon extraction for the three selected towns of analysis. Values are slightly off due to spatial averages from the polygon extraction, but these differences were relatively similar. Sometimes due to variations in individual raster cells, point extractions can yield abnormal results; this was not the case in this study.

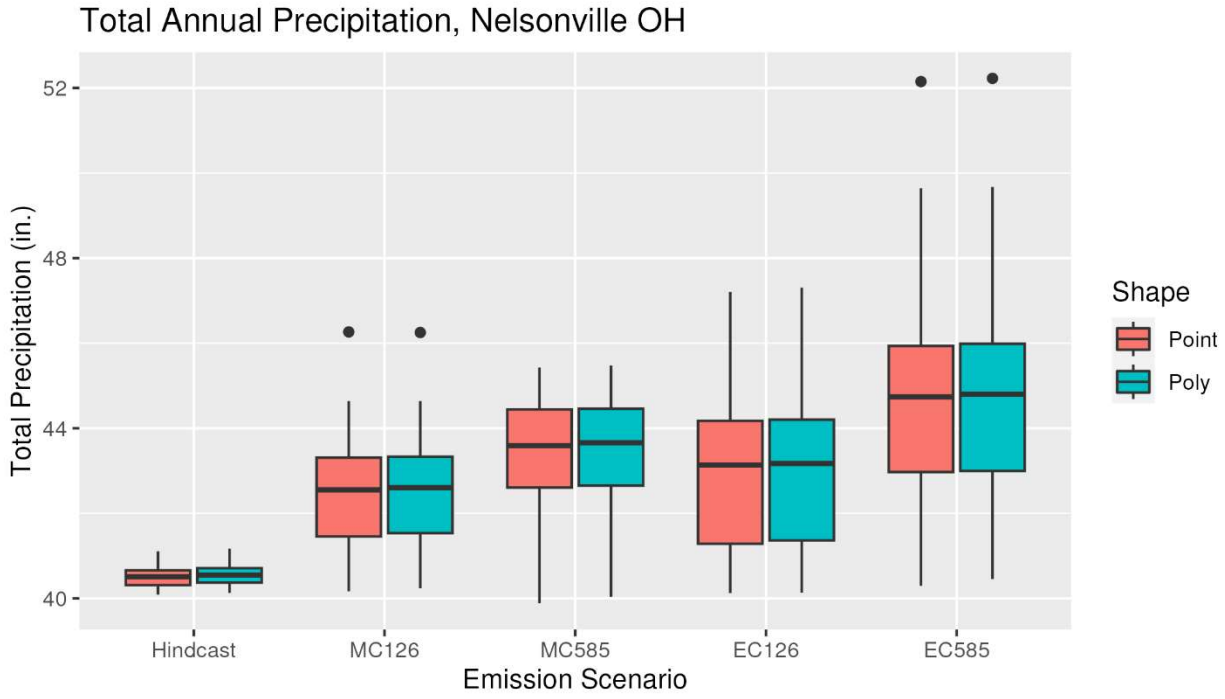





Average Annual Maximum Temperature, Nelsonville OH
Maximum Temperature (F)
76
72
68
Hindcast
MC126
MC585
EC126
EC585
Emission Scenario
Shape
Point
Poly


Total Annual Precipitation, Pulaski VA
Total Precipitation (in.)
51
48
45
42
Hindcast
MC126
MC585
EC126
EC585
Emission Scenario
Shape
Point
Poly


Total Annual Precipitation, Williamsburg WV
Total Precipitation (in.)
56
52
48
44
Hindcast
MC126
MC585
EC126
EC585
Emission Scenario
Shape
Point
Poly


Total Annual Precipitation, Nelsonville OH
Total Precipitation (in.)
52
48
44
40
Hindcast
MC126
MC585
EC126
EC585
Emission Scenario
Shape
Point
Poly